LOCATION, DURATION, AND POWER;

HOW AMERICANS' DRIVING HABITS AND CHARGING

INFRASTRUCTURE INFORM VEHICLE-GRID INTERACTIONS

by

Nathaniel S. Pearre

A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Marine Studies

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DEDICATION:

To my mother Anja,

my father Sifford,

and my wife Laural.

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ABSTRACT

The substitution of electrical energy for gasoline as a transportation fuel is an initiative both with a long history, and one made both pressing and important in today's policy discussion by renewed interest in plug-in vehicles. The research presented in this dissertation attempts to inform the policy discussion for governments, for electric utilities, for the makers of electric cars, and for the industries developing and planning charging infrastructure. To that end, the impacts of variations to several possible system design parameters, on several metrics of evaluation, are assessed. The analysis is based on a dataset of vehicle trips collected by Georgia Institute of Technology, tracking almost 500 vehicles that commute to, from or within the Atlanta city center, comprising Atlanta 'commuter-shed'. By assuming that this dataset of trips defines the desired travel behavior of urban and suburban American populations, the effects of travel electrification in personal vehicles can be assessed.

Several significant and novel findings have emerged from this research. These include the conclusion that at-work charging is not necessarily the logical next step beyond home-charging, as it will in general add little to the substitutability of electric vehicles. In contrast, high power en-route charging, combined with modest power home charging is shown to be surprisingly effective, potentially requiring of EV drivers a total time spent at en-route recharging stations similar to that for liquid fueled cars. From the vehicle marketing perspective, a quantification of the hybrid household effect, wherein multi-vehicle households own one EV, showed that about a quarter of

all households could adopt a vehicle with 80 miles of range with no changes to travel patterns. Of interest to grid management, this research showed an apparent maximum fleet-wide load from unregulated charging of about 1 kW per vehicle, regardless of EVSE power or EV battery size. This contrasts with a potential late night load spike an order of magnitude higher under certain time-of-use charging algorithm implementations. Finally, an EVSE and EV power capacity of 10-12 kW was shown to be a likely optimum if grid services from modulated charging are being considered.

Chapter 1

INTRODUCTION AND LITERATURE REVIEW OF VARIABLE GENERATION

This dissertation is informed by five areas of research in electric power systems and in personal transportation: management of high-penetration variable generation (such as wind and solar generators), the use and value of storage in the electric power system, patterns of private light vehicle use, vehicle design, infrastructure and operational requirements for electrically driven vehicles, and evaluation of the environmental impacts of switching from gasoline or diesel to other fuel sources. Correspondingly, this dissertation's literature review is broken up into several sections in the first three chapters. The first chapter examines variable generation and the problems it entails for grid stability. Chapter 2 reviews the literature surrounding vehicle driving patterns and charging loads, and what is being done to find solutions to the possible problem of charging load peaks coincident with existing late afternoon or early evening load peaks. The third chapter looks at the environmental effects of light vehicle electrification, as it exists today, based on an electric grid that still generates electricity primarily from fossil fuels. The third chapter also compares the effects of electricity production with other proposed gasoline alternatives, though most of them face significant technological, logistical, and/or economic hurdles to adoption that are at least as complex as those faced by electricity.

Within chapter 1, Section 1.1 is an introduction, comparing in broad terms the electrical and automotive sectors. Section 1.2 discusses some of the literature relating to variable generation, the problems with integrating it into the electric grid, and the effects of transmission. In section 1.3, energy storage, one of the solutions discussed in section 1.2, is explored in greater depth. Section 1.4 is a discussion of electrical energy storage as it applies to shorter timescales, both from the perspective of the capabilities of specific technologies and from that of grid services.

1.1 Introduction to Electricity and Automobiles

The industries and infrastructure comprising the electrical system, and those comprising the personal transportation system, have much in common. Both require massive capital investments, manage stupefying sums of money, and employ workforces that number in the millions within the United States alone (Kempton, Tomić 2005b). Of greater consequence, both of these systems evolved over the last century in an environment of cheap and readily available fossil fuels, a pre-condition that strongly influenced their development. Due to the long timescales of infrastructure planning, the prospect of constricting supplies of fossil fuels, along with our increasing understanding of their negative consequences, require that both of these industries plan for the era when such inexpensive energy sources are no longer available, or are restricted by policy. An additional important feature that these two systems share may provide a mechanism for both to reduce their dependence on fossil energy in concert: Both systems have substantially more energy conversion capacity than is needed to meet average demand, but for very different reasons.

In the case of the electrical industry, the need for over-capacity is due both to the non-storable nature of electrical energy, and due to our fluctuating amounts of consumption. For every electrically powered device that gets switched on, the mechanical load on a generator somewhere on the system is correspondingly increased, and its output must rise to match it[1]. This effect means that the demand for electricity, which fluctuates throughout daily, weekly and seasonal cycles due to daylight, temperature, weather variations, business cycles, and other factors, must be satisfied by generation and transmission sized for the highest load conditions, plus a margin for unexpected failures. The result is high system overcapacity to supply demand peaks that nationally trend to about 220% of average electrical load (EIA 2010) (Tables 8.1 & 8.11a).

In contrast to electricity, the production of other commodities and their flow from producers to consumers is moderated by both physical storage (warehouses, trains, trucks waiting to make deliveries) and by the laws of supply and demand; an increase

[1] There is a small amount of flexibility in the system, as electrical load manifests as a torque load on heavy spinning generating equipment; an imbalance between load and driving torque causes a minute angular acceleration, and a few moments of acceleration can be tolerated.

in demand for a good will increase the price, which will in turn moderate demand. For electricity however, these short-time fluctuations in the cost of supply are generally not reflected in the price of electricity paid by the end users, and even if they were, many of the fluctuations happen much faster than a human could response to market prices.

Within personal transportation, there is an even greater imbalance: The energy conversion capacity of the vehicle fleet is dramatically greater than the highest total instantaneous power demanded by the fleet for transportation (Kempton, Tomić 2005b). The nature of personal mobility leads to low utilization factors, roughly 1 hour use out of 24 in the US (USDOT 2009) (Table 15). In addition, the need of each vehicle to have the power capacity to meet maximum design load condition, such as accelerating onto a freeway or hauling a trailer uphill, has led to power capacity of light vehicles much greater than the average power used, even during that 1 hour of driving. As a simple example, consider a small gasoline vehicle with i) a 100 kW (134 hp) engine that ii) operates at an annual average 18% efficiency and iii) covers 20,000 km (12,500 miles) per year at iv) an average fuel economy of 7.8 l/100km (30 mpg). These values translate to an annual capacity factor of only 0.3%[2].

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[2] Total capacity is 100 kW x 8760 h/yr = 870 MWh/year. Utilization is found from i) fuel consumption (20,000 km x 7.8 l/100km = 1560 l gasoline consumed); ii) energy content of the gasoline (1560 l x 9.7 kWh/l = 15 MWh fuel energy consumed); and iii)

Both industries have historically required long planning horizons due to the capital-intensive operation necessary to achieve economies of scale, but the electric industry in particular has had to plan infrastructure looking forward in time several decades due to the high upfront costs and longevity of electrical generation and distribution equipment. The interaction of comparatively short life-span vehicles with the electrical infrastructure, as part of a broader shift of distributed generation and storage may begin to change that, but large centralized generation will likely always be an important part of the electrical system.

When discoveries in science or changes in public attitudes change the political landscape of the country, it may be necessary for government to step into the planning process of industry to drive it towards a condition, optimizing for formerly external costs. This has happened in the last few decades as a result of better popular understanding of the external social and environmental costs of the production of coal for electricity and the disposal of coal wastes (both airborne and solid), combined with the threats of climate change. In the automotive sector, many of the same concerns about pollution and carbon dioxide apply, as well as concerns of national energy security, energy independence, and the balance of trade and payments.

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assumed annual average efficiency (15 MWh consumed * 0.18 efficiency = 2.7 MWh delivered to the wheels): 2.7 MWh delivered / 870 MWh capacity = 0.3% capacity factor.

These concerns have led to a push for the deployment of renewable energy generation. However, as critics of renewable energy often say, 'the sun doesn't always shine and the wind doesn't always blow' (Svenvold 2008, Schlesinger, Hirsch 2009). Due to this intermittency of renewable energy sources, integrating them as a large proportion of generation risks destabilizing the grid. The limit of integration is often described as when installed wind capacity approaches minimum system load (Parsons et al. 2004, Ackermann et al. 2009) while levels of penetration above about 20-30% of energy production will affect costs associated with grid stability (Wargacki et al. 2012, Denholm, Hand 2011), although this number lacks a definitive analytical basis. Several strategies have been proposed for coping with the intermittency of renewable energy sources. Two of these proposed solutions are discussed in the following two sections.

1.2 Renewable Energy Transmission; the Dilution Solution

The transmission of electricity from a single generation site to a regional network can be done with relative ease where the infrastructure is in place. The advantage of doing so is that in principle, when wind speed (and thus power output) is low at one location on the transmission system, it may be high at another location, so renewable energy may be brought in from there. Several studies have been done recently on the smoothing effects of connecting wind power regionally via electric transmission.

Kempton et al. (Kempton et al. 2010) simulated a high capacity electrical interconnect along the east coast of the United States. They converted four years of nearshore wind data into power output of offshore turbines. The wind data were recorded by anemometers on NOAA's National Data Buoy Center buoys from 11 sites located off the east coast of the United States, covering roughly 1200 miles from Florida to Maine. The average or total output of the simulated transmission network exhibits far less variability and far slower changes in output than any of the individual sites. As is the case with almost all wind power installations, each of the eleven individual simulated wind farms is characterized by frequent periods of both maximum and of zero or near-zero output. In contrast, the interconnected system reaches its maximum output level at only a few isolated times, and in the four years of the analysis, the potential power output of the combined wind resource drops below 5% of system capacity only 1% of the time (Kempton et al. 2010).

A similar analysis of regionally aggregated land-based wind power looked at 11 years of data over the mid-west, the mid-Atlantic, and the North East (JCSP 2008). That study evaluated the regional wind resource as an interconnected whole and found that changes in total system output were much slower than any single site. Just like the Kempton et al. study (Kempton et al. 2010), however, the worst hours during the 11 years of data had negligible wind production regionally. This is of great significance, as the JCSP analysis is for a region with a similar spatial scale to that above, though extending both east-west and north-south, covering all the wind resources in an area of roughly 1,000,000 square miles.

Many other studies of aggregated wind farm sites have also found reduced variability, longer timescales of variability, and increased reliability, but indicate that full reliability is not practically achievable (Sinden 2007), possibly regardless of the degree of spatial aggregation and variability dilution (Czisch, Ernst 2001, Simonsen, Stevens 2004).

In assessing the variability of wind resources, singly or interconnected, it is relevant to consider that no system of electrical power generation is perfectly reliable. Coal generation, in particular, requires a significant amount of scheduled and unscheduled downtime for maintenance and repair. By comparing not the worst hour for aggregated wind output, but the 87.5% worst hour (equivalent to the average up-time of coal generation), Archer and Jacobson (Archer, Jacobson 2007) find that an array of 19 wind sites in the central plains states of Kansas, Oklahoma, Texas, and New Mexico produce 21% of their maximum rated power as "baseload". Regular maintenance of coal turbines can be scheduled to coincide with times of low anticipated load, however, and regular maintenance accounts for roughly ½ the down time, the other half being "unscheduled outages" (NERC 2008). In contrast, the vast majority of the down time of wind is unscheduled, mostly due to variations in wind speed, though unplanned changes in output are not instantaneous, and most of those changes can be predicted at least hours ahead of time. The Archer and Jacobson study used a single year of data, and found the worst hour of wind power output in their study had near zero total aggregated output (Archer, Jacobson 2007).

Designing networks of wind farms to optimize output variability, rather than simply to maximize annual output, is also a subject of interest. Cassola et al. (Cassola et al. 2008) examines the spatial distribution of a small 'fleet' of wind farms, and optimizes the distribution of a fixed total turbine capacity at different locations to reduce the aggregate power output fluctuations. In that paper the island of Corsica, a small isolated power system with a significant wind resource, was used as a case study.

The studies reviewed above have shown that the variability of renewable energy production can be reduced but not eliminated through spatial aggregation via power transmission, both in land based or offshore wind resources.

The same principle has been applied to load in traditional power distribution system analysis (Parsons et al. 2004, CAISO 2007). Load fluctuations occur as individual electricity-consuming machines are turned on or off. Aggregate loads generally take on a strong daily periodicity, with greater loads during the day, a weekly periodicity, with significant differences between weekdays and weekends, and significant annual variability, as heating and cooling loads rise and fall between summer and winter. Just as with renewable generation, the magnitude of these oscillations is reduced by connecting more and more disparate loads together.

As a thought experiment, we can imagine a perfect electric power network to interconnect wind generators that spans the globe, thereby eliminating effects of day and night, and windy or quiescent periods. Such a global transmission system would at best still only be able to get rid of fluctuations in wind generation. Even this would not be a full solution, as daily, weekly and seasonal changes in load, driven by uneven distribution of human populations and load centers around the globe would still cause aggregate load variability. Additionally, it is not simply an absence of variability in the load, or generation, that is needed, but a matching of load to variable generation. This suggests that transmission alone can never be an adequate solution to problems associated with either load variation, or intermittency of generation.

The potential of renewable energy technologies can be most harshly tested where systems are isolated from any connection to external electrical grids, thereby eliminating interconnections and transmission as a partial solution, or where the objective is the complete elimination of fossil fuel energy sources. A case study of such electrical systems on small Mediterranean Islands found that the total price of electrical could be reduced by adding batteries for energy storage, and using the energy storage to address the intermittency of renewable energy generation (Kaldellis et al. 2009). Island systems truly isolated from transmission are rare in practice, although they may be of interest to model as an extreme case.

In order to reach 100% renewable penetration in Denmark, Lund & Mathiesen (2009) used a diversity of renewable energy sources in their system model, including wind, wave, solar, and biomass for biofuels (Lund, Mathiesen 2009). Jacobson & Delucci (Jacobson, Delucchi 2011), like Lund & Mathiesen (Lund, Mathiesen 2009), were able to simulate a grid that did not rely on any fossil resources, using “wind, water and sunlight", relying on long-term energy storage in the form of hydrogen gas. It is informative to note that in these examples of extreme cases, some form of energy storage was a necessary part of the energy system, and the problem was approached as a pure engineering exercise without consideration of economic optimization.

A related study examining the electrical grid in Nova Scotia, Canada, and the mandated renewable energy production which will largely come from wind is presented in the penultimate chapter of this dissertation (Pearre, Swan 2013b, Pearre, Swan 2013a. With permission from ASCE). The study found that intra-provincial transmission and wind energy project site selection are not adequate tools for integrating the required quantity of wind energy without dramatically increasing ramp rate requirements of the fossil generating fleet. With a large storage system, however, the potential exists to retire a significant amount of existing coal generation.

1.3 Multi-Hour Energy Storage

The most significant variability in the output of a single wind farm location occurs at frequencies associated with the passage of weather systems, whereby several days of windy conditions might be followed by several days of quiescent conditions. This fact, though it applies directly to a single turbine without the buffering effects of transmission (Section 1.2), suggests that storage that can store hold energy to replace several days of average output would be required to fully level wind intermittency. It should be noted that in an integrated grid, there would inevitably be some 'dilution' of the output variability due to transmission, decreasing both the amplitude and the rate of power output fluctuations, but increasing the timescales over which those fluctuations occur.

Storing enough energy to back up even a single windmill for several days is a challenge. A simple comparison to a familiar 'large' storage device illustrates the challenge: a water tower, a human-made device that stores water at height, is comparable in size to a wind turbine.   If the tank of a water tower measures a little over 10m in diameter and is roughly 10m in height, it then contains 1E3 m3 of water. That water, at 1000 kg/m3, has a mass of 1E6 kg and weighs roughly 10E6 Newtons. If the tank is supported at a height of 20m, then the potential energy contained in that elevated water is 200E6 Joules, or ~55 kWh. The stored energy, therefore would cost only a few dollars as electricity. By comparison, a 2 MW wind turbine at a capacity factor of 0.33 produces, on average, 660 kW, or 660 kWh/hour. If the goal of the water tower is to fill in production gaps of that turbine to the level of average output, then the 55kWh of stored energy (assuming no conversion losses) would only last 55/660 or 5 minutes. So, even a large water tower can only smooth the output of a wind turbine on timescales of minutes, not nearly hours or days. Clearly a much larger storage resource is needed.

On the electrical demand side, timescales of variability in demand, other than the very large fluctuations that occur on 1-year periods, correspond to Van der Linden's 'Energy Management', with dominant periods of 12 and 24 hours (van der Linden 2006). It is worth noting that, while these event periods are not as a general rule significant to wind power variability, they do correspond to tidal power (either 6.125, 12.25 or 24.5 hour periods depending on the tidal regime) and solar power (24 hours). Storage technologies suited to timescales of several hours, which will be discussed later in this section, are therefore of great interest, in that they are correspondingly well suited to deliver power in a fashion that compliments fluctuations in load or shorter scale, non-synoptic wind fluctuations.

1.3.1 Pumped Hydro

Within today's electric systems, the predominant form of storage is pumped hydro (PH). It uses the same basic principles of energy storage as the hypothetical water tower analyzed in the prior subsection, that is, it can absorb and discharge electricity by pumping water to, and discharging from, an elevated reservoir. It is not volumetrically dense storage however, as demonstrated with the water tower analysis in section 1.3 above. To reach practical levels of storage, PH requires land forms with dramatic elevation changes between suitable geography for both upper and lower reservoirs. When such advantageous land features exist, the storage potential can be scaled to hundreds or thousands of MWh and achieve round trip efficiencies ranging from 65-80% (Levine 2011, Levine 2007).

Even without a lower reservoir, the application of conventional hydroelectric plants to meet fluctuating grid loads is in many respects a form of energy storage, lacking only the ability to be a negative producer (i.e., a load). As of 2008, there was approximately 20 GW of pumped hydro storage in America. Like all extant energy resources however, each facility is operated without specific regard to balancing the production of variable generation, focusing rather on revenue generation by operating to provide different services in their regional ISO energy market, or operating to meet requirements of an integrated utility. Increased renewable penetration will increase the revenue potential of energy storage by increasing the volatility of hourly energy prices, which some analyses indicate are currently insufficient to make storage financially viable (Ekman, Jensen 2010). Variable generation will also increase the demand for ancillary services such as regulation and reserves, which will be discussed below with respect to storage technologies less well suited to long timescales. This suggests that variable renewable generation will 'naturally' make use of existing storage resources that rely on arbitrage of hourly price differentials as one of their revenue markets (Denholm 2008).

1.3.2 Compressed Air

Another energy storage technology garnering a lot of interest is Compressed Air Energy Storage (CAES). CAES has the potential to scale to sizes relevant to renewable balancing, because as the name implies, energy is stored simply as pressurized air. Large volumes of compressed air may be stored in tanks or natural underground caverns at low costs and with minimal environmental impact (Cavallo 1995, Cavallo 2007), and may be discharged through a turbine to subsequently generate electricity. When the air is released back to ambient pressure, it will cool, reducing its efficiency and risking damage to generating equipment if icing occurs.

Thus, to more efficiently extract energy when a zero-carbon system is not required, the stored high-pressure air may be used to supercharge the combustion chamber of a natural gas turbine.

In a CAES system, air may be compressed either by electric compressor operated when electricity is cheap, or at least in principle, directly in a wind turbine system (Ingersoll, Marcus 2008). Though only demonstration scale CAES facilities have been built to date, there is a large potential for further expansion of the technology, capitalizing on natural underground 'salt domes' which are often left behind by petrochemical extraction (Cavallo, 1995; Cavallo, 2007).

Recovering and storing the heat generated during compression can improve the thermal efficiency of these systems. By approaching adiabatic compression, the need for combustible fuel can be eliminated, making a truly dispatchable renewable energy system (Ingersoll, Marcus 2008, Bullough et al. 2004). There is a significant amount of interest and development of this technology. LightSail Inc. has developed a small, modular, semi-adiabatic storage system the size of a shipping container that can be deployed at renewable generation sites, within the transmission system or at the end of distribution lines (Crane, Fong & Berlin 2011, Stahlkopf et al. 2011). Manufacturer's claims indicate that a 70% round trip efficiency is possible with this technology (LightSail Energy Inc.). Isolated system models, using a single generation source coupled with compressed air energy storage, have been shown to be capable of roughly doubling system capacity factor at low overall energy cost, or net savings if transmission is a significant fraction of total system cost (Cavallo 1995).

1.3.3 Solar Thermal (Production Side Storage)

Variable renewable energy sources that are to some degree synchronized with variations in load are, even if not technically dispatchable, of great value to grid operators. One of the most promising semi-load-matched renewable energy technologies is solar thermal, and many configurations of solar thermal can incorporate storage very simply. For example, by including insulated tanks into the hot side of the plumbing circuit of the working fluids of solar thermal energy systems, energy can be stored as sensible heat (Tripanagnostopoulos, Souliotis & Nousia 2002). These systems are currently commercial, and are now being incorporated into new solar thermal plants in order to delay peak output from solar midday, when maximum solar power is available, to the air-conditioning summer load peak in the afternoon and early evening. One of the first such systems was designed with 3 hours of storage (NREL 2010), enough to improve load-following somewhat. A more recent project includes 7.5 hours of storage, enough to dramatically improve the demand matching of solar energy production (Solar Millennium Staff Report 2008, Rovira et al. 2011).

1.3.4 Electric Thermal (End Use Storage)

Conceptually similar heat storage technology has been developed for the electricity end user, to take advantage of time-of-day energy pricing for hot water and space heating in buildings. While consumer prices vary around the country, in jurisdictions where utilities have instituted time-of-use pricing, night-time rates for electricity can be half or less of the on-peak rates, a differential of as much as 10¢ - 15¢ per kWh in the United States. In parts of Europe with significant penetration of intermittent renewable resources such as Germany and Denmark, there is likewise growing interest in end-use storage for integrating variable generation (Lund, Kempton 2008, Stadler 2008).

Typically end-use thermal storage systems have used storage media such as rock or phase change liquids. While the latter permit high specific energy with lower sensible heat, and thus lower energy loss through heat leakage, early solar systems using phase change materials required substantial ongoing maintenance. Thus, more recent commercial building heat storage has more often used sensible heat storage, i.e. heating a thermal mass to a high temperature. A recent development has been to use electric resistance heating to heat high-density, high specific heat ceramic blocks, resulting in a reduction of the physical size of systems. Because of the high temperatures possible with such a system, a relatively small mass and volume system has comparatively high energy capacity. This technology makes it practical to heat a home from stored heat for 18 hours, using a mass-produced system with no moving parts and minimal space and maintenance requirements. With 18 hours of storage, electricity purchases for home heat can be entirely shifted to lower 'off peak' rates at night. My examination of this technology with Mr. Steffes suggests that it could be expanded to store enough heat for several days with modest additional cost (Steffes 2008). The energy stored in the systems can be accessed throughout the day, or with appropriate controls, during wind lulls, by pumping a working fluid (e.g. air or water) over the heated bricks.

1.3.5 Chemical Batteries

Batteries store energy electrochemically and provide an alternative to the pumped hydro and CAES that is not dependent upon topography, uses no fossil-fuels, and is easily scalable. These features enable battery placement at the generation, transmission, distribution, and end-use levels (Spider9 2013). For the multi-hour timescales relevant to renewable integration, there has been some development of high energy-to-power ratio battery systems. Large, stationary batteries that can deliver power levels relevant to the grid for periods long enough to address daily load peaks require specific chemistries. Four battery chemistries of interest are:

- Lead-acid; a mature technology and industry
- Lithium-ion; an evolving technology in commercial production
- Sodium-sulfur; a fairly mature technology with commercializing production
- Vanadium redox flow; a developed technology, but with little industrial maturity.

Lead-acid batteries have been used in systems up to 40 MWh, demonstrating round trip efficiency of 72% (Parker 2001, Rodriguez, Spindler & Carr 1990), and have been show to last through a design life of 9 years (Wagner 1997), though longer application life may be realized with more modern batteries (GNB 2008, GNB 2002). Commercial lithium-ion cells have achieved very high power densities at 2000 W/kg, as well as high power to energy ratios making them suitable for second/minute timescale utility services (A123 Systems 2008), discussed in section 1.4. Sodium-sulfur batteries operate at 300°C in order to keep the electrolytes liquid (Takami, Takayama 2003). They have been used in large-scale storage such as the installed 34 MW / 245 MWh system operating alongside a 51 MW WTG farm (Roberts 2009).

Developments in grid-focused battery energy storage have produced "flow batteries", in which the energized electrolyte is a liquid and can be moved past the electrodes and stored in a tank of arbitrary capacity. Energy storage (kWh) and facility power (kW) can therefore be scaled independently to suit the duty cycle of the application, the power being determined by the size of a stationary electrode stack (McDowall 2006). Flow batteries have demonstrated over 10,000 complete discharge cycles (Prudent Energy 2011), an advantage they have over some of the more established battery chemistries.

Additional description of battery technologies for grid level energy storage is given in (Leadbetter, Swan 2012). Continual improvements in chemical battery technologies and ongoing reductions in cost have made batteries a more economically viable energy storage option. Where the energy's end-use is not necessarily heat (as is required for TES), or where geological or hydrological resources needed for pumped hydro or

CAES do not exist, battery energy storage for grid stability is becoming and ever more popular and practicable option.

1.4 Shorter Timescales of Storage and Grid Services

Besides compensating for the unsynchronized power output of renewable resources, there are several kinds of grid service that could be addressed efficiently using storage, differentiable in their technical requirements by their timescales of variability. We have already discussed storage for timescales associated with meteorological events (days) and daily load fluctuations (hours) for which Van der Linden (van der Linden 2006) uses the designations i) Energy Management. Beyond these he characterizes other services as ii) Bridging Power, requiring seconds or minutes of duration, and iii) Power Quality & Reliability, requiring only milliseconds to seconds of duration. For each of these timescales there are specific, though overlapping, storage technologies (McDowall 2006) and electrical system services (Ribeiro et al. 2001).

Shorter timescale storage, corresponding to the energy services described by Van der Linden (van der Linden 2006) as ‘Bridging Power’ are also of great interest. They are useful for addressing the rate at which generation output increases or decreases, known as “ramp rates”, which has traditionally been associated with faults, and can be another undesirable effect of renewables (see chapter 11).

Currently the most valuable electric power services purchased by Regional Transmission Organizations such as PJM and CAISO is “Frequency Regulation” (Kempton, Tomić 2005a, Letendre, Denholm & Lilienthal 2006). The frequency regulation market is designed to compensate for short term changes in electrical load or generation, or more generally, mismatches between scheduled generation, and load. Such unplanned variations in load and generation can be either positive or negative, so in many jurisdictions the command signal for frequency regulation is designed so as to be symmetrical about zero, making it at least nominally energy neutral, and a good candidate for energy storage (Kempton, Tomić 2005a).

In 2011, the Federal Energy Regulatory Commission required changes to the market of Frequency Regulation to reward fast and accurate response to the command signal (FERC 2011). Though pricing and valuation structures are still being worked out, some analyses suggest that very fast response resources might present a value to the system of between 2 and 17 times their nameplate capacity (Makarov et al. 2008), depending on the specifics of the system in which they work and the role with which they are tasked and might therefore result in a 40% reduction of regulation procurement (Texas Energy Storage Alliance 2010). Another analysis finds it is possible that storage resources capable of very fast response times (such as batteries and flywheels) may be paid six times the regular rate for regular performance (Rastler 2010). This would make this a very lucrative market, though limited in size. The first steps at implementing a market design that would encourage and capitalize on the capabilities of storage were in the Midwest ISO (MISO) December 18th, 2008 (Texas Energy Storage Alliance 2010).

For such short timescales, a different suite of storage technologies, better suited to the task, is available. One is flywheel energy storage, which is being advanced specifically to address the frequency regulation market, with systems designed to have 15 minutes of full power before exhausting their storage (Beacon Power). In a flywheel system, which at utility scale consists of a building containing dozens or hundreds of individual flywheel units, energy is stored as rotational kinetic energy. In the current generation of advanced flywheel systems, composite rotors spin on magnetic bearings in a near vacuum, so that very little energy is lost to friction.

Another solution being developed and deployed specifically to compete in the regulation market is, once again, batteries (Chatterjee 2011). The term 'batteries' can describe a number of different technologies and particularly chemistries that store electrical energy as chemical energy (Divya, Østergaard 2009), the most important of which from an industrial readiness perspective were covered in section 1.3.5. For the regulation market, since the energy throughput can be as high as 2 Wh/W per day[3], there is a great premium on battery cycle-life (in contrast to the batteries in many

[3] Based on my own unpublished analysis of frequency regulation signals.

consumer goods such as laptops, which need only last a couple of years with less than one cycle per day).

Chapter 2

INTERACTIONS BETWEEN PLUG-IN VEHICLES AND THE ELECTRIC GRID

In this, the second of three chapters providing background information and reviewing literature applicable to this dissertation, I review prior studies that describe observed and potential interactions between plug-in vehicles and the electrical grid. In section 2.1, the concept of using the distributed batteries of electric vehicles in roles supporting the electrical grid is discussed. Section 2.2 reviews the literature on use patterns of privately owned vehicles, and the corresponding potential grid impacts of vehicle electrification. Section 2.3 covers the literature of vehicle charging modulation and control, which are described collectively in this document under the term ‘charging algorithms’. Section 2.4 reviews literature and empirical evidence about the energy consumption of electric vehicles. Finally, in section 2.5, previous academic literature assessing the marketability of electric vehicles is addressed, added because the ability of electric vehicels to meet individuals’ travel requirements (referred to throughout this dissertation as ‘EV substitutability’) and market penetration of electric vehicles defines the magnitude of their potential impact.

2.1 Multi-purpose Battery Storage: Vehicle Energy Storage

In a report released in 2009, the Pacific Gas and Electric Company stated that over 70% of automakers were developing vehicles that will plug in to the grid, and that will use grid electricity for some fraction of their motive energy (PG&E 2009). As of this writing (2013), Chevrolet, Fiat, Ford, Honda, Mitsubishi, Nissan, Smart, Toyota and Tesla all sell vehicles in the US that plug in and use grid electricity for at least some of the distance they travel, and more are on their way. This activity in the automotive sector is in fact the latest in a long history of interest in development of 'modern' electric cars, interest that began with the oil crisis in the 1970s. Any vehicle that can use grid electricity for propulsion must have some amount of onboard electrical energy storage. With the introduction of tens of thousands of these vehicles in 2013, and presumably hundreds of thousands over the next few years, the cumulative potential of battery energy storage systems increases dramatically.

In the same way that residential TES (Section 1.3.4) has a potential system cost advantage over purpose-built industrial storage because the incremental cost to homeowners is small (who must have domestic heat anyway), using electric vehicles it is possible to provide grid services using batteries that have been bought primarily for other purposes. Thus, while battery energy storage for grid services has historically been expensive, and dedicated banks of batteries intended solely for grid services still are, using the batteries in a fleet of electric cars has the potential to avoid most of those costs. Proponents of using cars as a distributed network of energy storage devices recognized that such a distributed fleet could displace city power stations, reduce the loading on transmission and distribution systems, clean the power supply, and provide black start capability, among other benefits (Lachs, Sutanto 1995).

If such a potential were realized in even a small fraction of the light vehicle fleet, it could have an enormous impact on the electrical system, as the energy conversion capacity of light vehicles is an order of magnitude greater than that of electrical generation (Kempton, Letendre 1997). In its more basic form, the distribution utility could have control over the charge timing of plug-in vehicles, allowing the utility to smooth the power distribution curve by adding load to the periods when it would otherwise be at its lowest (Letendre, Denholm & Lilienthal 2006), while at the same time affording the vehicle owner access to the lowest possible cost energy for transportation (Denholm, Short 2006).

An additional step of complexity, utility, and value would be to enable the vehicles to 'push' electricity from the on-board storage back to the grid. The term for this capability is Vehicle-to-Grid, abbreviated V2G, in reference of the direction of power flow (Kempton et al. 2001). This capacity is required for many of the system benefits of grid-tied battery storage envisioned by Lachs & Sutanto (Lachs, Sutanto 1995), and many of the required power electronics and control system components required for this functionality in vehicles are discussed by Lachs *et al*. (Lachs, Sutanto & Logothetis 1996). By including back-feeding capability, not only can periods of low electrical demand (or price) be exploited to charge in order to later provide transportation, but system load during periods of high demand can also be reduced by discharge to the grid. Of even greater financial value are grid services such as frequency regulation and spinning reserves, which are stand-by power services intended to compensate for unexpected fluctuations in load and supply, respectively (Kempton, Tomić 2005a). Interestingly, the value of these services is generally unknown in fully regulated and vertically integrated utilities, so it was not until the deregulation efforts associated with the Energy Act of 1992, and subsequent Federal Energy Regulatory Commission orders in 1996 (FERC 1996), that the value of these services were made apparent by market valuation in the United States.

One workable and marketable system for contracting and delivering these services from a distributed fleet of privately owned vehicles has been described as an "aggregator". An aggregator would have to be an entity that can establish individual contracts with, and manage the communication with many individual vehicles, and individual contracts with utilities or transmission authorities (Kempton, Tomić 2005b), though several others operational models have been proposed (Kempton et al. 2012).

The flexibility of such a resource could in principle be expanded dramatically by including plug-in hybrid vehicles that can generate electricity from gasoline or gaseous fuels (Kempton, Letendre 1997, Kempton et al. 2001). In such a model grid entities could draw not only stored electricity, but also could direct distributed resources to turn on their engines and generate 'new' electricity to supply load peaks. More recently, however, risks associated the remotely controlled combustion of fuels (or non-combustive oxidation in the case of a fuel cell), and the associated generation of combustion byproducts (e.g. fumes accumulating, or oxygen exhaustion, in a garage), may explain the lack of further policy research and technology development using liquid or gaseous fueled vehicles for grid services.

2.2 Vehicle Use Patterns, Recharging, and Grid Availability

Though not of direct concern to automakers, the timing with which electric vehicles plug into the electric grid is of great concern to electric industry. Some of the reasons for this concern are described in section 2.3. Additionally, time-of-day patterns of driving and parking are central to the discussion of electric vehicle batteries used as energy storage resources. Thorough analysis of these is currently hobbled by an incomplete and inadequately characterized understanding of the usage patterns of cars. Much of the data available to vehicle manufacturers comes from U.S. Bureau of Transportation Statistics, which provides less insight into distributions of usage patterns, such as those that might inform electric vehicle design, than it does about average values.

More detailed information about driving patterns is scarce. Long term, large sample data is most economically collected by automated means, for example by instrumenting vehicles with logging GPS systems. Unfortunately, such studies are expensive and it is difficult to develop a representative dataset, due to the invasive nature of the observations. One important finding to date from such studies is that the fraction of vehicles in use at any one moment rarely exceeds 20% of the vehicle fleet (Gonder*et al.*, 2007; Pearre*et al.*, 2011). This finding suggests that potential grid resource from vehicles with energy stores will be significant, because even at times of peak vehicle use, the great majority of vehicles remain parked. (This conclusion relies on those parked vehicles being connected to the grid, which is an assumption subject to further study by this dissertation). Most studies that attempt to evaluate the time-varying nature of plug-in vehicle impacts on the grid do not use empirical large-sample driving data, but assume load profiles based on simplifying assumptions and stereotypes about driving patterns and charging algorithms (Hadley, Tsvetkova 2009, Lemoine, Kammen 2009).

Without the expense and complexity of logging GPS systems, a substantial improvement on retrospective survey data can be achieved with driver travel logs referred to as 'travel diaries' and phone interviews. Axsen&Kurani (Axsen, Kurani 2008) use such self-reported vehicle travel data, in conjunction with a web-based survey of 2,373 new car buyers to construct vehicle fleet electrical load curves. They also use parking location information to calculate the fraction of vehicles that have access to a plug on weekdays and weekend days. Their results suggest that with unconstrained charging, a significant load peak would result from vehicles plugging in at home on weekday evenings, between 6 and 8pm. They find that the peak would not be diminished much by the availability of plugs at work or other frequented locations. They conclude that their findings underscore the need for charging controls on electric vehicles.

Several studies have been done relating to the abilities of alternative fuel vehicles to provide the transportation services currently supplied by gasoline cars, some aspects of which may be considered useful to the analysis of electric vehicles and EV charging infrastructure.

In considering literature relevant to this dissertation, one can find many studies of introducing new fuels and energy carriers. However, studies relating to alternative fuels such as hydrogen (Schulte, Hart & van der Vorst 2004, Nicholas 2004, Williams, Kurani 2006, Nicholas, Ogden 2006, van Bree, Verbong & Kramer 2010, Li, Ogden 2011) and bio-ethanol (Ogden, Steinbugler & Kreutz 1999, Yacobucci, Schnepf 2007, Wakeley et al. 2008) are of only modest relevance, since in either of those cases, vehicle use and refueling is determined by the need for new, purpose-built fuel distribution infrastructure. The one area where alternative liquid fuel literature may be of relevance to EV adoption is in the area of fast-charger deployment, which will be examined in more detail in section 7.3. For example, refueling studies suggest that most gas-station visits occur within 3 – 7.5 minutes' drive of either a trip origin or destination drivers (Nicholas 2004, Kitamura, Sperling 1987, Melaina 2003), and that only a small minority of refueling trips are not part of some other travel (Kitamura, Sperling 1987).

Another confounding factor to the applicability of other alternative fuel studies is that in general liquid fuels fill quickly, with average gas station visits lasting only 5.6 minutes (Adornato et al. 2009), whereas electricity fills slowly, imposing some unique constraints. The comparison can be quantified by reviewing that US law (40 CFR 80.2) limits gasoline pumps to 10 gallons/minute, or 37.8 l/m, providing an energy transfer of 357 kWh/minute, or 21.4 MW[4]. In contrast, SAE J1772 defines Level II charging rates up to 80 amps at 240 volt (19.2 kW), and the most aggressive plans call for on 120kW fast chargers (Tesla Motors 2012), although Tesla's system is currently compatible only with their own cars. Since electricity delivers approximately 4 times more travel per unit energy onboard the vehicle, gasoline's comparative fueling rate is effectively 5.3 MW, or 275 times faster than the fastest US J1772 electric facility, or about 50 times faster than the fastest DC charging. On the positive side of electricity as a fuel, virtually every home and every business in the United States has electricity, and about half of new car buying households already have access to a 120V plug within 25 feet of their home parking (Axsen, Kurani 2008). Marketing materials of automakers estimate that installation of a 240V charging system would add costs on the order of 5 – 7%[5,6] to the total upfront costs of an electric vehicle.

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4 Sporadic testing by the author and others has found 7.5 gal/min (15.3 MW) fairly consistently at non-randomly sampled gas stations.

5 Announcment at Consumer Electronics Show, Jan. 2011, Las Vegas, accessed 7/10/2011 http://www.plugincars.com/best-buy-provide-ford-focus-electric-charging-stations-lower-prices-competition-106640.html

6 Nissan Inc., from company web siteAccessed 7/10/2011 http://www.nissanusa.com/leaf-electric-car/index#/leaf-electric-car/estimator/index

2.3 Charging Algorithms for Electric Vehicles

The importance of the driving patterns (or conversely, the patterns or availability for grid service or grid loading) is made doubly important when one considers the three dramatically different possible effects of electric vehicles on the grid. One possibility is an undesirable spike in load that could potentially occur if charging rates and timing are unconstrained, referred to here as ‘dumb charging’. The second is that, by the use of a simple timer, such a coincident early evening load peak is avoided, but no more finely tailored benefits can be realized. The third possibility is that the load from EVs will be managed by some combination in-vehicle intelligence and real-time control, possibly charge and discharge control, and such cars will become resources providing valuable grid services.

Some grid managers and policy makers are focused on only the first of these three possibilities, with concerns that uncontrolled charging of vehicles might place excessive peak-coincident load on the grid. This scenario assumes a large number of vehicles arriving at their destinations and plugging in at roughly the same time. The prototypical example imagined is the evening rush-hour; returning from work and plugging in at roughly 6 pm when grid loads in many areas are already at or near their peak. The possible effects of such ‘dumb’ charging have been demonstrated at even very low plug-in vehicle market penetrations for particular markets (Hadley, Tsvetkova 2009, Lemoine, Kammen 2009, Parks, Denholm & Markel 2007, Kelly

2009, Pearre et al. 2011), particularly with regard to impact on the distribution infrastructure (Shao, Pipattanasomporn & Rahman 2009).

In contrast, some studies performing system-wide or generation-side analyses conclude that approximately 70% (Pratt et al. 2007) or 84% (Kintner-Meyer, Schneider & Pratt 2006) of the light vehicle fleet could be charged from the spare capacity of the electric system, if charged off-peak. Denholm& Short (Denholm, Short 2006) found less surplus electrical capacity, enough to power 40% of the mileage of 50% of the vehicle fleet. For 'dumb charging', Ford (Ford 1995) found that just 20% of the vehicle fleet could be charged overnight without overburdening the then extant grid in southern California. While the reasons for these significantly divergent estimates is not clear, even 20% of vehicles represents an enormous market that would take decades to fill at the current rate of market growth of plug-in vehicles. As a point of comparison, Toyota reported that as of the spring of 2012, after more than a decade on the market, they had sold a total of 4 million Prius hybrids worldwide (Toyota Motors 2012), while 20% of the US vehicle fleet would be more than 40 million vehicles. Regardless of the exact percentage, as more electrically driven vehicles are sold, it will be important that vehicle charging become more intelligent than 'dumb' battery devices, which begin charging when first plugged in and charge at a fixed rate until the battery is full.

Several research groups have proposed policies and have begun work to develop algorithms for charge modulation to address these concerns. As discussed in section

2.1, Lachs*et al*. (Lachs, Sutanto & Logothetis 1996) and subsequent studies have identified myriad possible benefits for distributed battery energy storage systems, most of which could be provided by vehicle batteries. These benefits, however, must all be considered as secondary to the primary application of electric vehicle batteries – providing transportation service for drivers.

Preserving this transport function while maximizing the provision of electric system services is a balancing act controlled by the charging algorithm of each vehicle. Some proposed designs of charging algorithm use existing information and existing market structure. The first, Kempton &Letendre (Kempton, Letendre 1997) proposed to interact with hourly energy pricing in the day ahead market, purchasing energy at night when it is inexpensive and selling all but the evening's driving needs during the afternoon when energy prices are high. Refinement of that model by the same research group (Kempton, Tomić 2005a) recognized that many existing energy markets provide enough value in fast response services that trading on energy (kWh) prices is less important. Those researchers began the work of delivering models whereby that value can be realized in a market, and part of the value returned to the car owner (Kempton, Tomić 2005b).

Other applications of charging modulation that rely on real-time load monitoring are also possible. A home or residential area control system has been proposed that could be tasked with flattening the load peaks found at the individual household or neighborhood level (Mets et al. 2010). For example, considering Plug-in Hybrid

Electric Vehicles (PHEV), at market penetrations of 10, 30, or 60% of the vehicle fleet, they found that charge-management would have the ability to reduce the load peaks by 8 – 42% compared to 'dumb' charging scenarios (Mets et al. 2010).

The first researchers to write about the application of distributed vehicle batteries to grid service wrote about the benefits of such a system before the concept of the smart grid was being widely discussed, but many of the functions they envisioned would necessitate the kinds of information about grid capacity that did not exist in most areas at that time (Kempton, Letendre 1997, Lachs, Sutanto & Logothetis 1996). With the emergent concept of the smart grid, the mechanisms of realizing these benefits have been fleshed out. These include smart-grid enabled management of grid congestion (Galus, Andersson 2008), which in turn would make available the benefits of transmission upgrade deferrals (Kempton, Letendre 1997). Caramanis& Foster (Caramanis, Foster 2009) take a conceptually simpler approach, proposing a system of charging rate management aimed at both minimizing the cost of energy to vehicle owners while operating in frequency regulation markets and managing distribution congestion.

Systems that combine multiple services that may at times make competing demands on a vehicle's batteries may become difficult to manage. Galus&Andersson (Galus, Andersson 2008) introduce the concept of agent based interactions between vehicle control 'agents', representing the interests of the vehicle owner, and 'Plug-in Hybrid Electric Vehicle (PHEV) Manager' agents that negotiate and aggregate vehicles into a useful resource. Using a charging only model (as opposed to a 2-way power flow model), and a price-driven (as opposed to dispatch or Automated Generation Control) model, Galus&Andersson(Galus, Andersson 2008) describe vehicle agents that develop a demand function for electricity that compares current prices against the proximity of upcoming needs, and negotiate decision to charge or not charge according to that negotiation. The concept of agents negotiating for value to determine the operation of vehicles is extended not only to broader energy markets, but also to the increased economic value of Vehicle-to-Grid by Kamboj*et al*. (Kamboj et al. 2010). In both cases, these negotiations rely on the vehicle agent having some predictive capability of upcoming transportation energy needs, which may be derived from learning predictive software onboard the vehicle, or a much simpler scheduling or calendar system driven by user inputs.

A step in the right direction has already been incorporated into vehicle designs; commercial systems using driver input, but not predictive functions, are used for pre-departure temperature adjustment in production electric cars (Evans 2011). Existing system use knowledge of upcoming trips only for the benefit of the driver, by increasing vehicle range (by avoiding depleting the battery for temperature control where possible), and increasing driver comfort. Such a mechanism being extended to improve the possible benefit to grid operators seems eminently possible if a market mechanism incenting the drivers to participate were in place.

2.4 Determining Electric Vehicle Energy Consumption

In performing an analysis that includes comparing travel distances with electricity consumption and grid impacts, a pivotal parameter is the amount of electrical energy that is required to propel a car a given distance. This conversion factor will be used throughout this dissertation. The value that will be used is based on several sources, including vehicle specifications, owner data, manufacturer data, government ratings, and also prior literature. It should be noted that we focus on those numbers intended to apply to compact or mid-sized personal vehicles. For medium duty vehicles such as large pick-up trucks, vans and commercial vehicles, electrical energy use per unit distance will be higher., Though their ability to serve electrical capacity markets may be significant on a per-vehicle basis due to having large batteries and high power electronics, they will likely be a smaller proportion of the fleet, and are not analyzed in detail here.

The most direct data is that which has been gathered by our own research group; the vehicle-to-grid research group in the Center for Carbon-free Power Integration at the University of Delaware maintains a fleet of 3 AC Propulsion eBoxes being used as V2G development platforms (in addition to 20 BMW Mini-Es that are not in regular use). These vehicles have provided valuable data, and other empirical, historical, modeled, and tested data exist for other electric vehicles. These data, derived from total available stored energy and reported vehicle range, are presented in Table 1 (Pearre et al. 2011).

Table 1: Energy use of electric drive vehicles (from Pearre et al. 2011).

Vehicle	Usable Battery Capacity	Range	Energy Consumption
GM EV-1 Pb-A[7]	18.7 kWh	55 - 100 miles	187 – 340 Wh/mile
GM EV-1 NiMH	26.4 kWh	75 – 150 miles	176 – 350 Wh/mile
Th!nk City[8]	24 kWh	100 miles	240 Wh/mile
Nissan Leaf[9]	24 kWh	100 miles	240 Wh/mile
Nissan Leaf[10]		71 miles	340 Wh/mile
Mitsubishi iMiEV[11]	16 kWh	100 miles	160 Wh/mile
Mitsubishi iMiEV10		53 miles	300 Wh/mile
AC Prop. eBox[12]	35.0 kWh	130 - 150 miles	233 – 269 Wh/mile
Tesla Roadster[13]	53.0 kWh	227 miles	233 Wh/mile
Tesla Roadster10		189 miles	280 Wh/mile
Aptera 2e[14]	10.0 - 13.0 kWh	100 miles	130 Wh/mile
GM Volt[15]	10.4 kWh	40 miles	260 Wh/mile
GM Volt10		29 miles	360 Wh/mile

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[7] Wikipedia: GM EV1. From [en.wikipedia.org/wiki/EV1], ranges reported by lessees.

[8]Th!nk Vehicles: www.thinkev.com, range quoted as "up to 100 miles" on ECE-R101 driving cycle.

[9] Nissan Motors: www.nissanusa.com/leaf-electric-car/, range on LA4 driving cycle.

[10] U.S. EPA; www.fueleconomy.gov

[11] Mitsubishi Motors: www.mitsubishi-motors.com/special/ev, range on Japan 10-15 driving cycle.

[12] AC Propulsion, Inc: www.acpropulsion.com/ebox/index.php

The reported and calculated energy efficiency of EVs seems to show a wide range, from 130 to 360 Wh/mile. The very low consumption per distances in this Table are for the iMiEV, probably not a realistic value since this number is from a very small car tested on a very forgiving driving cycle, and to the Aptera 2e, an extreme design dramatically optimized for aerodynamics and low weight. The very high consumption reported in Table 1 for the EV1 may in part be due to inefficiencies in their power management and drive system (from a personal communication with Tom Gage, then president of AC Propulsion), while the calculated values used by the EPA seem to only poorly reflect drivers' experiences. Thus, ignoring the outliers, energy consumption by small electrically driven vehicles tends to be in the range of 230 – 300 Wh/mile. This suggests that a value of 280 Wh/mile may be a reasonable representative value for use in this dissertation.

Previous studies of electric vehicle operation have used values similar to those reported in Table 1. A California Energy Commission study (CEC 1992) assumes small EV energy consumption will result in a range of 4.17 miles/kWh, which

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13 Tesla Motors, Inc: www.teslamotors.com/learn_more/faqs.php, range on 2008 EPA test driving cycle.

14 The Daily Kos: www.dailykos.com/story/2009/2/5/145733/6076/1000/693621

15 General Motors: http://gm-volt.com/2010/10/26/chevrolet-volt-will-utilize-10-4-kwh-of-battery-to-achieve-ev-range/

corresponds to 240 Wh/mile. Denholm& Short (Denholm, Short 2006) follow the precedent of EPRI and use 250 Wh/mile for small vehicles and 420 Wh/mile for "large SUVs", giving a fleet average of 340 Wh/mile. Axsen&Kurani (Axsen, Kurani 2008) survey previous research and use an energy consumption of 260 Wh/mile. The Electric Power Research Institute uses 280 Wh/mile in a related analysis for light vehicles (Graham 2001), though in subsequent years they too used 260 Wh/mile for compact sedans (Duvall 2002).

It should be noted that a few other studies assume much higher energy consumption values, from 400 to 750 Wh/mile. A number of such studies dating from the 1970's through early 1990's are reviewed in Ford (Ford 1995), who finds that many of those studies assume larger vehicles, and almost all assume the then-dominant, lead-acid batteries, which due to their low energy mass density (i.e., great weight) would contribute to lower vehicular energy efficiency. Subsequent analysis within that study assumed small EV energy consumption of 240 Wh/mile (Ford 1995).

In sum, this literature review corroborates the user-reported energy efficiency review summarized in Table 1 above, that 280 Wh/mile is a reasonable representative value for small electrically driven vehicles.

2.5 Market Penetration Potential of Electric Vehicles

The magnitude of the effect that electric vehicles could have on the electric grid, either for good (Section 2.4) or for ill depends on the number of them on the streets and plugging into electrical outlets. There are several potential constraints on the sales of electric vehicles, including the ability of limited range vehicles to deliver the transportation services people need, the availability of charging infrastructure to vehicle owners, and of course considerations of potentially higher upfront costs (notwithstanding potentially lower operating expenses), compared to conventional vehicles. There are also far less quantifiable effects related to brand confidence, feature content, and vehicle styling, but any conclusions about those would be highly speculative.

It should be noted that grid services could potentially be provided by any vehicle with a power-cord connected to the grid, including not just Electric Vehicles (EVs), but also Plug-in Hybrid-Electric Vehicles (PHEVs) (Galus, Andersson 2008). PHEVs combine the benefits of internal combustion drivetrains, such as energy dense fuels and existing ubiquitous fast-refueling infrastructure described in section 2.2, with some of the benefits of electric drive such as regenerative braking, smooth operation, and lower energy costs. However they also include some of the negatives of conventional vehicles, such as maintenance requirements and systemic complexity associated with including, operating, and insuring the emissions compliance of an internal combustion engine.

Many of the issues associated with EV marketability, such as necessary range and recharging infrastructure availability are not applicable to PHEVs, which do not require recharging via a grid connection for continuous operation, and are not constrained in travel range by the size of the electricity storage or currently sparse recharging infrastructure. As a consequence, the economic tradeoffs of battery cost, size and weight will probably favor smaller batteries in PHEVs (Graham 2001, Slater, Dolman 2009, Shiau et al. 2009, Tamor, Gearhart & Soto 2013). This conclusion is significant to this discussion, as small batteries are limited in their ability to provide grid services, and small batteries, it may be presumed, make investment in high-power charging infrastructure (including charging hardware within the vehicle) less economically sound. If it is correct that most PHEVs will have less battery energy capacity and lower charge/discharge power capacity, the benefit to PHEV owners of providing grid services would be limited, and thus their power and energy characteristics will not be analyzed in as much detail in this dissertation (Kempton, Tomić 2005a).

Much of the research into EV and PHEV market size has focused on travel data and driving range. As discussed above, authoritative national data on driving patterns is collected and disseminated by the National Highway Traffic Survey (USDOT-BTS 2003, USDOT 2009). The NHTS driving range distribution data for commute trip was reportedly used by automaker General Motors in designing their PHEV, the Volt. By providing electricity storage sufficient to propel the Volt 40 miles, GM’s intent was to be able to satisfy 78% of American commuters using only electricity (Dennis 2010). However, the same NHTS survey data suggests that only 18% of US automobile trips are work-related, compared with 44% family or personal (e.g. shopping) and 27% social or recreational (USDOT-BTS 2003).

The evaluation of the market for EVs is more challenging than simple driving range measures, because vehicle substitutability relies not only on the average travel distance, but rather on the high end of the travel distance distribution. Even public opinion surveys may be uninformative, since the experience of owning an electric vehicle is foreign to most survey respondents or vehicle buyers. This possibility is supported by the conclusion of a study by the UK's Technology Strategy Board that prior to participation in an EV study, 100% of new private drivers reported anxiety about reaching their destination, while after three months of driving EVs, that fraction dropped to 35%, despite no change in daily driving patterns (Everett et al. 2011). Rather than opinion studies, constraints may be applied to known demographic and travel pattern information to set bounds of possible EV adoption. The studies reviewed below take this approach.

Nesbitt *et al.*, (Nesbitt, Kurani & DeLuchi 1992) impose a severe set of constraints on potential EV buyers including i) home ownership, ii) the presence of a carport of garage at the primary residence, iii) at least two vehicles owned by members of the household, and iv) a commute of less than 80 miles round trip. Using these restrictions applied to the 1985 American Housing Survey, the study authors found a market size of 28% of US households (Nesbitt, Kurani & DeLuchi 1992).

More recent studies have attempted to refine our understanding of the constraints that could limit plug-in vehicle adoption. Relying on their own survey tailored to household / EV compatibility, Axsen&Kurani (Axsen, Kurani 2008) found that more than half of the new car buying public have an electrical outlet within 25 feet (7.6m) of their principal parking location. This was assessed from survey and interview data from 2,373 households in the United States. Looking only at driving ranges, Pearre*et al.* (Pearre et al. 2011), found that 9% of vehicles in greater Atlanta, Georgia never exceeded 100 miles of distance driven in a day during a one-year monitoring period, but that that number could be increased to 32% never exceeding 100 miles by assuming that drivers would tolerate vehicle substitution or modification of their travel plans on six days each year.

In terms of market penetration, Duvall (Duvall 2006) predicted that PHEVs could capture 25% of the new vehicle market in certain regions of the country by 2018. This projection agrees well with the 28% suitability findings of Nesbitt *et al.* (Nesbitt, Kurani & DeLuchi 1992) described above, and has been adopted by several other researchers for use in evaluating grid impacts (Hadley, Tsvetkova 2009, Shao, Pipattanasomporn & Rahman 2009). It is relevant to note that 25% market share is an enormous number of vehicles, an order of magnitude greater than the market share that non-plug-in hybrid electric vehicles have achieved after 12 years of widespread availability (Toyota Motors 2012). Reaching 25% of new vehicle sales would be a very substantial achievement.

By contrast, a survey of literature on CO_2 reduction technologies found that new car sales of EVs are expected (or projected) to rise slowly in Europe to only about 5% or less in the next fifteen years (Nemry, Brons 2010). The study models several possibilities of battery price, energy density, and charging infrastructure developments, and computes electric vehicles market shares of between 0.5 and 29%, depending on those factors, with 5% used subsequently as an assumption for CO_2 reduction. A similar literature review for PHEV sales finds predictions that average to about 10% market share by 2025. Their own evaluation predicts PHEV market shares between 5% and 32.6% based on the same battery and charging infrastructure options used in the EV sales model (Nemry, Brons 2010).

A particularly interesting scenario exists for multi-vehicle households, which make up the majority of households in many developed countries. The scenario of a household having access to at least one vehicle able to fuel quickly enough to have functionally unlimited range, and one range limited EV has been termed a 'hybrid household', the implicit analogy referring to the fact that members of the household can shift from electricity to gasoline based on their range needs (Kurani, Turrentine & Sperling 1996). For example, a GPS-based travel record of 255 households in Seattle, concludes that a 100 mile range EV could be suitable for 80% of multivehicle households while only requiring four (4) days of travel adaptation a year (Khan, Kockelman 2012).

Chapter 3

THE ENVIRONMENTAL EFFECTS OF ALTERNATIVES TO GASOLINE

In this, the final chapter of literature review, the environmental effects of powering the personal vehicle fleet with energy sources other than gasoline and diesel are discussed. In section 3.1, I examine the specific case of substituting electricity for gasoline, using electricity from the existing grid in the United States (electricity as transportation energy source is the main subject of this research). In section 3.2 a comparison between different types of electrified vehicles is presented, specifically electric vehicles (EVs) and plug-in hybrid vehicles (PHEVs). Finally, in section 3.3 I provide a survey of the environmental impacts of alternatives to gasoline other than electricity.

3.1 Environmental Effects of Private Vehicle Electrification

The electrification of transportation is popularly expected to have beneficial net pollution effects, but opponents of the technology often point out the "long tailpipe" argument; that electricity in the United States is produced in large part by burning coal, a notoriously dirty energy source. By powering cars with coal rather than gasoline, the argument goes, emissions are simply moved from the car's tailpipe to the coal plant's smokestack. More careful analysis of the electric grid and vehicle use is necessary to evaluate the probable change in pollutant emissions due to changing motor vehicle fuels.

Several studies attempt to deliver more precise evaluations by focusing on smaller regional and state specific environmental impacts, and evaluating a correspondingly more tightly defined network of electrical generators. Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) are frequently used as regions for such analyses, since these institutions generally have consolidated records of energy bidding, unit commitment, and facility-specific emissions profiles.

The system operator in California, the California Independent System Operator (CAISO), has jurisdictional boundaries similar to those of the state, and has been the subject of many such regional studies. There are many reasons to think that California will be a strong initial market for electric vehicles: it has historical been a test-market, it has large population of technophiles and early adopters, it has some of the most stringent environmental regulations in the world (Jansen, Brown & Samuelsen 2010), and much of the state by area, and the vast majority by population, has mild climates which promote battery health (Zhang, Wang & Tang 2011).

With a known network of generators and knowledge of system dispatch ordering, the greenhouse gas (GHG) emissions profile of CAISO can be modeled hourly, and the additional GHG impacts of additional load computed with accuracy. Such studies indicate that the California grid will likely produce between 475 kg CO_2/MWh (Jansen, Brown & Samuelsen 2010) and 724 kg CO_2/MWh (Axsen et al. 2011) for the marginal electrical load imposed by PHEV charging. The later study compared this to the existing gasoline-powered fleet, which averages 28.8 mpg, and concluded that electrically driven miles produce 30-38 % less GHG emissions per miles driven. The variation within that range in Axsen *et al.* is due to changes in 'all electric range'

(AER) of the PHEVs, and at what times of the day vehicles are charged, which influences the exact generation mix that produces their electricity.

Axsen *et al*. also note that the GHG emissions, when attributing GHGs from only the marginal units to PHEVs (rather than the average units which are on average cleaner in CAISO), are about the same as those of existing low consumption gasoline powered vehicles, with a CO_2 footprint equivalent to 42.5 mpg (Axsen et al. 2011). This is roughly the same conclusion reached by Samaras & Meisterling in a lifecycle analysis of GHG production associated with PHEVs (Samaras, Meisterling 2008).

Another ISO particularly well suited for such analysis due to its electrical isolation from the rest of the country is that of Texas. The state of Texas not only has its own ISO (ERCOT), but is also its own interconnect, i.e., its electrical system is connected to the rest of the electrical grid in North America only by a small number of DC interties. When 20% of the vehicle miles travelled (VMT) in Dallas/Ft Worth, Houston, Austin, and San Antonio are powered by electricity produced at night, a significant reduction in GHG and a small reduction in NOx emissions result (Thompson et al. 2011). These results seem to be sensitive to charging scenarios, however, as 'convenience charging', with late morning and early evening load pulses, slightly increased ozone exposure (which is tied to NOx emissions) at several monitoring stations. Another study only evaluating nighttime charging, and only in the Austin, TX metropolitan statistical area likewise finds small averages decreases in emission of NOx (and correspondingly ozone) due to transportation electrification

(Alhajeri, McDonald-Buller & Allen 2011). Reductions in other pollutants are also found in that study, including average carbon monoxide (CO) reductions of about 7% (Alhajeri, McDonald-Buller & Allen 2011).

One less-discussed aspect of the 'long tailpipe' argument is that the eponymous tailpipe has the potential to carry pollutants away from people. Thompson *et al.* find that pollution exposure in the cities of Texas is reduced proportionately more than the emissions themselves (Thompson et al. 2011). Similarly, Kintner-Meyers *et al.* find in a nationwide study that human exposure to all pollutants improve as the emission sources shift from million of tailpipes to a comparatively small number of large power plants (Kintner-Meyer, Schneider & Pratt 2006). In both cases this result is attributable to generation facilities generally being situated in areas of lower population density, while areal vehicular emissions are very closely tied to population density.

All of the above-mentioned studies make the apparently reasonable assumption that additional charging loads due to PHEV use will increase the NOx emissions of the electric generation fleet proportionally to increased electricity production, or to production at the marginally dispatched generators (even while reducing NOx from vehicles). This may not be the case, however, as another study of the Texas grid suggests that the load control possible with PHEV charging, discussed in more detail in section 2.3, may facilitate more efficient generating unit operation (Sioshansi, Denholm 2009). By using an economic optimum system dispatch model with managed PHEV charging, Sioshansi & Denholm find that PHEVs reduce the need for partial-load operation of generating units, a condition during which the NOx emissions may be significantly higher than during full power operation. This effect only applies to low and moderate PHEV penetrations however (<15% or so), after which point the greater total energy production drives emissions back above the no-PHEV case.

The above discussion focuses on the California and Texas electrical systems (or certain regions within them), both of which are more reliant on natural gas, a relatively clean-burning fuel, than the United States as a whole. The effects of travel electrification in other regions where coal is a much more important energy source is therefore likely to be less positive, and germane to the broader discussion.

When the fuel substituted for gasoline is coal, as it likely would be in the PJM balancing area (consisting of much of the northeast north of Washington D.C., east of Chicago, and south of New York state), the emissions effects of travel electrification are less uniformly positive. Thompson *et al.* (Thompson, Webber & Allen 2009) find that when charging requires additional nighttime production of coal electricity, concentrations of criteria pollutants would decrease in widespread and densely populated urban areas but increase significantly in localized areas near generation facilities. Peterson *et al.* (Peterson, Whitacre & Apt 2011) likewise look at the PJM and NYISO (with a jurisdiction consisting of the state of New York) areas and find that, counter-intuitively, the greatest reductions in CO_2 in PJM are realized from unconstrained charging: When vehicle charging loads coincide with high system loads, the marginal generation is more likely to be from cleaner burning natural gas fired power plants.

Even more coal intensive than PJM generally, is the state of Ohio. As Thompson *et al.* and Alhajeri *et al.* found for PJM, the majority of the electricity used in travel electrification in Ohio would derive from coal, making it in many respects a worst-case scenario analysis. Sioshansi *et al.* (Sioshansi, Fagiani & Marano 2010) find that when charging occurs at times of minimum load (overnight), coal supplies 96% of the energy and CO_2 reductions are negligible compared to the existing vehicle fleet. Even in Ohio, however, when charging occurs during existing load peaks, coal supplies 'only' 83% of the energy, and the CO_2 footprint of each mile travelled is reduced by 24%. In contrast to the results of the above-mentioned studies, Sioshansi *et al.* find that in Ohio the emissions of criteria pollutants (specifically SOx and NOx) are dramatically increased by travel electrification, a finding consistent with the other literature reviewed here.[16]

While results may be more precise in a regional or ISO-based study, and may be more appropriate for some criteria pollutants, concerns of GHG are not just regional in

[16]This result may be improved by recent EPA rule changes removing 'grandfathered' status of antiquated emissions controls on many of the nation's dirtiest coal plants. (US-EPA 2011)

nature. Kintner-Meyers *et al.* evaluate unused grid capacity in 12 NERC regions in the eastern and western interconnects, and likewise find that PHEVs, or more generally travel electrification in personal vehicles, always reduce greenhouse gas (Kintner-Meyer, Schneider & Pratt 2006). As the contrasts between the ERCOT, JPM and Ohio studies indicate, Kintner-Meyers *et al.* find that NOx emissions may increase or decrease dependent region's reliance on coal. Kittner-Meyers *et al* also find that SOx and particulate emissions increase in the majority of regions. In a similar analysis of the nationwide generating fleet, Stephen & Sullivan (Stephan, Sullivan 2008) find greater variability in the GHG reduction potential of travel electrification, but point out that greater GHG reductions would be possible by building new, more efficient generation, even coal-fired units to replace the existing coal fleet, much of which is over 40 years old. The grid is, in fact, getting cleaner, under the pressures of new air quality rules, incentives for renewable generation, increasing size and lower costs of renewable energy, and decreased viability of new coal generation given both regulatory constraints and the lower cost of natural gas. One might also expect that additional generation would be needed to meet charging loads, but that may not be true in the short- and medium-term (Kintner-Meyer, Schneider & Pratt 2006, Ford 1995, Denholm, Short 2006).

In conclusion, the emissions impacts of travel electrification are mixed. Improvements in GHG emissions are promising, with electrified miles seeming to offer a 5-50% reduction in GHGs, depending on region. In contrast, emissions of criteria pollutants are less positive. In some cases (principally SOx and particulates) they can be dramatically higher (Kintner-Meyer, Schneider & Pratt 2006), while in others (NOx) reductions depend on the grid mix (Peterson, Whitacre & Apt 2011). Perhaps the greatest promise for environmental benefits of travel electrification is not in the travel at all: The ability to manage grid loads for the efficient (and economic) dispatch of existing resources could facilitate a greener grid with very little in the way of capital upgrade (Sioshansi, Denholm 2009). Further, the ability of managed PHEV or EV charging to facilitate variable renewable penetration (section 1.3) could, in conjunction with the above-mentioned motivations for more renewable generation, contribute to a cleaner grid for all electricity users (Denholm, Short 2006).

3.2 Distinguishing Pure EVs from Plug-In Hybrids

The extent to which EVs and PHEVs differ in terms of environmental impacts depends primarily on the emissions associated with travel electrification. Some consideration has to be given to environmental impacts elsewhere in the vehicles' lifecycles, but those will be a small part of each vehicle's overall impact (Samaras, Meisterling 2008). In section 3.1, the effects of electricity powered miles were discussed at length, with the conclusion that absolute emissions levels were mixed (electric miles reduce GHGs and usually NOx, but increase SOx and particulates, particularly around the generators).

The effects of travel electrification on emissions are related to the composition of the generation fleet that makes up the marginal generation requirements, as discussed in section 3.1. As such, differences between the environmental impacts of EVs and PHEVs are determined by the overall fraction of vehicle miles travelled (VMT) that can be electrified by each kind of vehicle, referred to as the "utility factor" (Bradley, Quinn 2010).

Analysis of utility factors for PHEVs indicates that, depending on the availability of charging, about 26 – 44% of VMT would be electrified by a PHEV that can power the first 10 miles of travel on electricity (a PHEV-10) (Axsen et al. 2011), while 50 – 80% of miles could be electrified by a PHEV-25 (Bradley, Quinn 2010) and a PHEV-40 would electrify 62 – 79% of miles (Axsen et al. 2011). Khan & Kockelman (Khan, Kockelman 2012), likewise fine that in a single vehicle household, a PHEV-40 would permit the electrification of 80% of traveled miles, and 50 – 70% of miles as the preferentially chosen vehicle in a multi-vehicle house. Above about 100 miles of range, PHEVs would deliver more than 85% of miles from electricity. For such long-range PHEVs, small variations in utility factor were observed related to vehicle age, average annual mileage (which is correlated with vehicle age), and charging infrastructure. Shiau *et al.* note however, that while larger batteries may reduce lifetime GHG emissions (to a point) lifetime costs are minimized by opting for smaller batteries (PHEV-25 – 50, depending on battery price) and using the battery more intensively (Shiau et al. 2010).

Corresponding modeling of the usability of pure EVs requires a few more assumptions, the most important of which is that for all household (or individual) trips within the range of a particular EV will be taken by an EV. This appears to be the case, as EV user trials found no significant decrease in daily VMT among EV drivers (Golob, Gould 1998). The range of the EV used in that trial was not explicitly stated, but can be inferred to be greater than 100 miles from the travel pattern results presented. A more recent study of EV-100 use in Berlin found that an "a range of 140 – 160 km is sufficient for everyday ", and estimated that 80% of all study participants' travel were accomplished in their EVs (Cocron et al. 2011). Thus, a PHEV-40 and an EV-100 seem to have about the same capacity to displace gasoline VMT, and may be reasonably used as the basis of comparison.

The fixed (non mileage related) environmental costs associated with PHEVs and EVs derive from their manufacture and disposal. Samaras & Meisterling (Samaras, Meisterling 2008) follow a derivation of battery manufacture energy for PV systems (Rydh, Sandén 2005), which indicates that each kWh of battery requires primary energy of 470 kWh, equivalent to about 13 gallons of gasoline. More recent analysis concluded that battery manufacture for an EV would contribute 15% (Notter et al.), or 28% (Majeau-Bettez, Hawkins & Strømman 2011) of the environmental impacts attributable to the vehicle. Roughly halving the size of the battery to produce a PHEV-40 rather than an EV-100 would therefore reduce environmental impacts by about 9 – 16%, a significant, though not overwhelming value. Importantly, the environmental impact of manufacturing internal combustion engines and the various systems associated with their use (fuel, oil and air filters, gas pumps, emissions control systems etc.), have not been evaluated, and no thoroughly researched values were found in the reviewed literature.

In conclusion, the relative environmental impacts of PHEVs and EVs are unlikely to be dominated by the greater manufacturing impacts of a larger battery, especially as manufacturing processes mature and the embedded energy of battery capacity falls. Furthermore EVs, to a greater extent than PHEVs, will drive consumers to smaller, more energy efficient vehicles to avoid upfront costs, which may make per-electric-mile emissions lower for the EV fleet than the PHEV fleet. As the electrical mix incorporates more variable renewable electricity generation the advantage in terms of environmental footprint of both PHEVs and EVs over conventional vehicles will increase. Finally, this analysis has ignored the secondary grid-cleaning potential of V2G, for which EVs will have greater capacity due to larger batteries and higher power connections, which will be discussed in greater length in Chapter 9.

3.3 Evaluations of Alternative Fuels other than Electricity

The question of indirect effects of transportation energy choice were explicitly and intentionally excluded from the review of emissions effects of electricity generation presented in section 3.1. However, an evaluation of such effects is a necessary component of the broader question of how alternative fuels might change the environmental impacts of our energy and transportation systems as a whole. Comparing electricity generation to the tailpipe emissions resulting from the combustion of liquid fuels alone neglects too broad an array of upstream and downstream environmental impacts, including land use change and water resource issues. It is also difficult to evaluate this question without an *a priori* comparison of these different kinds of impacts.

Evaluating the well-understood Texas grid and Austin, Alhajeri *et al.* (Alhajeri, McDonald-Buller & Allen 2011) compare partial fleet electrification and a complete transition to an 85% ethanol (E85) fleet, to a base case of gasoline powered vehicles. They find that when PHEVs provide 17% of VMT from electricity, travel electrification reduces criteria pollutants and ozone more than a complete switch to E85. Compared to a national analysis, this conclusion may be somewhat optimistic though, since the generation mix in the Austin area is much more reliant on natural gas than the national average (57% vs. 23%), with significantly less coal (22% vs. 45%) (EIA 2010).

Once celebrated as the cure of all energy ills, the 'hydrogen economy', which could include hydrogen fuel cell hybrids or hydrogen ICE vehicles for personal transportation, would be both very energy intensive and correspondingly intensive in GHG emission. Heracleous (Heracleous 2011) investigated various operations within the well-to-wheels generation, conversion, and use of H_2, and found GHG emissions of 180 g/km (similar to a gasoline burning vehicle getting 50 miles per gallon) are needed for processing the fuel. That study did find significant GHG reductions would be possible from generating H_2 from biomass feedstocks, down to about 90 – 110 g/km, though biomass feedstocks increased the total energy consumption significantly.

Natural Gas has also been touted as a clean burning and inexpensive fuel. Some claims for tailpipe emissions from CNG-ICE indicate a CO_2 reduction of 76% and reductions of criteria pollutants by 83-100% (Bakar, Sera & Mun 2002), though these estimates appear not to address upstream emissions. Study of hydraulic fracturing, a technique for improved natural gas recovery that has resulted in a natural gas boom in North America has been found to release enough methane at wellhead to raise total GHG impacts beyond those of coal (Howarth, Santoro & Ingraffea 2011). A study by Argonne National Labs (Wang, Huang 2000) evaluated a dizzying array of pathways by which natural gas could be used for vehicle propulsion, ranging from CNG-ICE vehicles, to NG fueled electric generation, through NG-based synthetic liquid fuels derived from currently flared wellhead gas. Their results suggest that CNG-ICE vehicles (such as the Honda Civic-NG which has been sold in parts of the United States for many years) reduce net GHG emissions by 10-15%. These contrast with 52-65% reductions in GHG emissions when NG is used to generate electricity specifically for EVs, a result slightly better than (though generally similar to) the reductions possible via any of a variety to solid-oxide based fuel cell technologies (Wang, Huang 2000).

While we often limit our attention to emissions into the air and water, water supply impacts also distinguish different energy sources. King & Webber (King, Webber 2008) evaluate conventional and unconventional fossil fuels, hydrogen fuel pathways, electric vehicles, ethanol produced using a variety of agricultural practices, and biodiesel, all by the metrics of water withdrawals (as for cooling a thermal process) and water consumption (as for irrigating fields). By these measures the best energy source for transportation is renewable-sourced electricity, while the second best is renewable-sourced hydrogen. Un-irrigated soy biodiesel and conventional fossil fuels follow not far behind, while conventionally generated electricity and any fuels that rely on it, are found to depend on water to supply the dramatic cooling loads of thermal generators.

Biofuels hold the promise of very high energy density combined with the potential of compatibility with existing fueling infrastructure, in some cases existing vehicle engines, and low environmental impacts. A recent review study by the EPA (Ridley et al. 2012) cautions that while CO_2 and other pollutant impacts of biofuels have been quite well studied, there are other aspects of their use that have gotten comparatively little attention. The authors particularly caution that the effects of biomass cultivation on biodiversity, trade, and human health are comparatively poorly understood.

With the majority of biofuels in North America being ethanol, a more detailed look at its production and the effects of its combustion is warranted. Ginnebaugh *et al* (Ginnebaugh, Liang & Jacobson 2010) find that several organic compounds with negative health impacts are produced in greater quantities by E-85 ethanol (85% bio-ethanol, 15% gasoline) than by conventional gasoline. In a subsequent study, Ginnebaugh and Jacobson (Ginnebaugh, Jacobson 2012) refine their previous results and finds that the interaction of fog and combustion products of either fuel produce harmful pollutants, with E-85 at lower temperatures, typical of those found during the winter throughout much of the country, being significantly worse than gasoline.

In conclusion it may well be the case that in the near term, and at small fleet penetrations, the most environmentally benign energy is (conventional) natural gas, especially insofar as the volumes of it currently flared as waste-products of petroleum exploration can be put to use (Bakar, Sera & Mun 2002). When burned in an ICE it is less expensive and far cleaner in all respects than gasoline, and when purified and used in a solid-oxide fuel cell as an electricity source for a hybrid it can return thermal efficiencies similar to those of the best combined-cycle NG generators. Scaling natural gas, however, quickly runs up against production limits, and the environmental effects of shale fracturing, about which far too little is know with certainty. NG in its simplest implementation (though not in its most efficient), NG-ICE, also has the benefit of requiring only a conversion of the existing vehicle stock, rather than its wholesale replacement.

In the longer term, proposed next-generation bio-mass crops and biofuels show great promise for near GHG neutrality and far greater yields than those of corn ethanol, or even sugarcane (Wargacki et al. 2012). The advantage of not requiring fleet replacement, for some biofuels even obviating modification to existing vehicles as is the case with butanol (Dürre 2007) is compelling, as is the convenience (and familiarity) of a relatively stable, nontoxic liquid fuel.

In the long term, however, it is all but inevitable that the electrical system will continue to become cleaner, as intermittent renewables will make up an ever larger portion of that system. In addition, electrified transportation has the potential to not only deliver low-pollution travel, but to help make all uses of electricity cleaner and cheaper. As a consequence of these factors, it is probably that electricity will be the most environmentally benign transportation energy if it isn't already. Perhaps the hybrid household of the future will have an EV for everyday use and an algae-biobutanol hybrid for long distance travel.

Chapter 4

DATA ANALYSIS; SOURCES, METHODS AND LIMITATIONS

This research effort is principally focused on two questions related to the adoption of electrically driven vehicles. One of these is extent to which EVs can be substituted for vehicles in the existing fleet, assuming that vehicle buyers and drivers do not face psychological barriers to long-distance travel. The second is the array of potential interactions between plug-in vehicles and the electric grid. To answer the second of these, I have attempted to quantify the potential of plug-in vehicles to either harm or help the system of electric generation. Harm could derive from unregulated charging adding a massive additional electrical load to existing peak loads on the grid, possibly exceeding generation, transmission, or distribution system capacities. Help could come in form of balancing services, load leveling or ramp rate attenuation, and potentially facilitating the integration of variable renewable energy sources. To evaluate the probabilistic and time-varying nature of these potentials, I will use historical data as a model of both vehicle fleet use and electrical systems to evaluate the interactions, and assess both beneficial and harmful impacts as a function of a set of variables. The primary data source, which defines the fundamental parameter of the model for the primary analysis of vehicle travel, energy consumption, and grid availability, is described below, along with the methods used in this analysis.

In section 4.1 of this chapter, I give a description of the origin of the data used in the formulation of the travel model, and compare it to other similar data sets from the literature. Section 4.2 is a discussion of the characteristics of the Atlanta and Georgia drivers who make up the sample population, and compares them to U.S. national averages in an effort to understand how well the results of this research can be applied to other part of the country or the world. In section 4.3 the first of the variables under investigation, charging infrastructure buildout, is presented as part of a description of the methods used to determine probable charging locations. In section 4.4, the second input variable is introduced; specifically the possible behaviors plug-in vehicles might exhibit upon plugging in ('charging algorithms'). In the final section, a detailed description of the operation of the model is given.

4.1 The Data, its Origin, and Comparison to Other Datasets

Many of the analyses undertaken in this study derive directly from the use patterns and energy consumption of the fleet of privately owned vehicles in America. The most authoritative and complete public data on vehicle driving patterns in the United States is available from the USDOT- Bureau of Transportation Statistics (USDOT-BTS 2003b, USDOT-BTS 2007), although most of these data are provided at an aggregated level. Where national or aggregated information of this kind is needed, or where points of comparison are needed to validate the data used for more detailed analyses, the Bureau of Transportation Statistics information will be used. However, for most of the data analysis undertaken for this dissertation research, the US DOT findings lack adequate specificity or an adequate characterization of the variability between drivers and between trips.

As part of a program to integrate the studies of traffic patterns, driver behavior and the air quality effects of vehicle emissions, a group at the Georgia Institute of Technology has compiled a detailed database of vehicle use (Wolf et al. 1999, Schönfelder et al. 2005). In contrast to most previous vehicle use studies that relied on self-reporting of trips or telephone interviews, this database was generated automatically by GPS-enabled data acquisition hardware installed in the subject vehicles. This dataset also contrasts with most of the contemporary and subsequent driving pattern studies using GPS, which record only a few days of travel patterns in sequence (Gonder et al. 2007). The equipment used to gather data for this study tracked each car in the Georgia data sample for more than a year. Demographic information about the household to which each vehicle belongs was also collected in subject interviews. For the duration of the study, whenever the ignition of an instrumented vehicle was turned on, the GPS receiver and computer in that vehicle would record vehicle position once per second (i.e. at 1 Hz) until the vehicle was once again switched off. These instrument installations were left in place until the battery powering the data acquisition computers failed, usually between 2.5 and 4.5 years. The result of this effort is many terabytes of data giving second-by-second vehicle positions, covering almost 500 individual cars over the course of multiple years.

Because the research performed at the Georgia Institute of Technology recorded information about the actions of real people going about their everyday lives, and because precise times, locations, and velocities of all trips could reveal private and even potentially embarrassing or incriminating information, it is subject to protection as a “human subjects” dataset. In accordance with this status, data about individual vehicles, vehicle operators and specific trips are not available beyond the walls of the server room at Georgia Tech, and all analysis of individual households or vehicles, for this or other studies, must happen in that room. As a consequence all data products distributed outside the Georgia Institute of Technology, including those presented in this research are aggregated into averages, distributions, or trends for the protection of the research subjects’ privacy.

For the analysis performed in this study, the portion of these data covering calendar year 2004 was selected, and collapsed into individual vehicle trips. Each ‘trip’ is defined as an instance of the vehicle’s ignition being turned on and subsequently turned off again. Each ‘trip’ is described by a start time and location, end time and location, distance covered, vehicle make, model & year, and is paired with the demographic information about the household. Part of the ongoing analysis at the Georgia Institute of Technology is the classification of recurring trip start and end locations as “Home”, “Work” and eventually other frequented locations. These characterizations are also included in the information defining each trip, but were not complete at the time that this research was conducted, so a substitute parking location analysis was constructed, described in section 4.3.

For the analyses presented throughout this dissertation, individual trips (key on to key off) separated by less than 30 minutes were concatenated into single, longer trips. The duration of each concatenated trip is the sum of the durations of the included trips and the durations of the included intervening stops. The concatenated trip distance is the sum of the included trip distances. This simplification was deemed appropriate because it was felt at the time that this research was being set up that short duration stopovers would have little impact on the investigation of serviceability of electric vehicles, since few drivers would plug a vehicle in during such a short stop. Thus, a "trip" is defined in its most basic form as the time and travel between two parking events of a duration of greater than one-half hour. Although the vehicles studied were gasoline vehicles, for the purpose of this analysis, a trip can be thought of as a time, distance, and discharge quantity between two potential charging opportunities. The interplay between actual charging opportunities and the definition of a trip is the subject of further discussion in section 4.3 and in Chapter 6.

4.2 Validity of the Model Source Data

As with any modeled system, the validity of the results depend on the accuracy, precision and extent of the data used to build the model. Assuming those 2004 data are representative of current and emerging conditions in the real world, and if the treatment of the data by the model are a reasonable representation of reality, then the results produced by the models will have validity.

The initial study on vehicle use and trip making behavior includes data from 484 vehicles. The study participants were selected using random stratified sampling (Schönfelder et al. 2005, Guensler, Williams & Ogle 2002). The sampling has been found to be reasonably representative of the demographic distribution of the greater Atlanta area, with a slight underrepresentation of lower income groups and corresponding overrepresentation of higher income groups. The travel statistics revealed in this dataset indicate that in terms of vehicle miles travelled, and trips per day, the people of Atlanta are slightly more reliant on personal vehicles than the American population as a whole, indicating that if there is a bias in the data used, it is a 'conservative' bias, producing results *less* favorable to either the adoption of EVs or to using those vehicles for energy services, when parked (USDOT-BTS 2003b).

It must be emphasized that the Atlanta driving data have not been demonstrated to be, and I do not assert that the findings of this research are representative of the diversity of car-buying consumers everywhere in the world, in other industrialized countries, or even in every region of the United States. In sparsely populated rural areas, such as the US Western interior states, where typical driving distances are substantially longer, a separate, rural data collection effort would improve representativeness for the rural portion of the population.

The sample used in this study draws from an area accounting for roughly half of Georgia's population, so a discussion of state wide characteristics has some relevance: The USDOT Bureau of Transportation Statistics indicates that Georgia as a whole has the 6th highest average commute duration at 27.2 minutes, behind New York (30.9 min), Maryland, New Jersey, the District of Columbia, and Illinois, somewhat above the national average of 25.0 min. (USDOT-BTS 2007).

In Georgia as a whole, personal vehicle mode-share for commuting is 78.2% v. 76.0% for the country as a whole (USDOT-BTS 2007). Georgia also ranks 7th in annual vehicle miles traveled per capita at 12,124. This is significantly greater than the national average of 10,067 (USDOT-BTS 2007). Consistent with the above facts, Georgians also own a lot of cars, as Georgia ranks 8th among the states by that metric with 1.39 registered vehicles per licensed driver. The national average is 1.19 cars per driver (USDOT-BTS 2007). It is important to note that with 20% more vehicle miles per capita than average, but 17% more vehicles per driver, vehicle miles *per car* should be quite close to the national average, based on statewide USDOT data.

Information about the metropolitan area of Atlanta is also available, and similarly suggests an active car culture: Among the 30 largest urbanized areas in the United States, Atlanta has the 5th most roadway per person at 4.5 miles per thousand people, behind Houston, Kansas City, Pittsburgh and St. Louis. Among the same 30 largest urban areas, Atlanta has the second highest daily vehicle miles traveled per capita trailing only Houston, TX. It also ranks 8th in daily traffic per freeway lane mile (USDOT-BTS 2007).

These statistics paint a picture of Georgia and specifically of Atlanta as a place where there are lots of roads, people have somewhat long commute distances and commute by car, so drive a lot of miles each year, and drivers tend to own several cars, yet neither the city nor the state is an outlier in any category. There is an extensive highway system (many lane-miles per person), but also a lot of traffic per lane mile, which presumably contributes to the fact that the people of Georgia spend a lot of time commuting. Generally, these statistics suggest that in most respects data from the greater Atlanta region will produce a result that is slightly less favorable for EV utility than the country as a whole, but should be reasonably representative.

4.3 Home and Work Locations.

One of the most interesting and least well understood aspects of EV adoption is the interplay of different levels of charging infrastructure (i.e., EVSE availability), and vehicle usability. For this reason, one of the variables investigated in the driving model described above in section 4.1 is charging infrastructure buildout. In order to populate the infrastructural development model, it is necessary to evaluate when vehicles are parked at locations that are likely to be sites for charging infrastructure, or 'Electric Vehicle Supply Equipment' (EVSE). As described above, ongoing research at Georgia Institute of Technology includes an effort to correlate frequented parking locations to zoning types and to individual buildings or parking lots. This effort is intended to establish an authoritative categorization of parking locations with location identities including home, work, school, shopping, movies etc., but it is labor intensive, exacting and slow work and was still incomplete at the time my most recent access to the database at Georgia Tech.

In order to conduct this analysis, I have constructed a simple algorithm to identify probable home and work locations, based on the assumption that they will be the two locations at which each vehicle is parked for the greatest, and second greatest cumulative amount of time. To do this the year was divided into 10-minute increments, and the most frequented portion of the geographic scope of the data (roughly 300 km x 370 km) was divided into a locational grid of roughly 50 meters x 50 meters. For each 10-minute time increment during which a particular vehicle was parked, the value in the parking location grid corresponding to the location where that vehicle was parked was indexed by one. As an example, if a vehicle spent 10 hours overnight parked at a certain location, that location within the matrix would be indexed by 60 (10 hours x 6 time increments per hour).

4.3.1 Home Locations

The location of a "Home" for each vehicle is identified as one at which i) that vehicle is parked for the greatest cumulative number of hours during the year of the study. After initial processing of the data corresponding to this definition, it was deemed necessary to add a second criterion to the algorithm. Thus home could also be ii) any other locations not already identified where the vehicle spends more than 25 nights (100 cumulative hours between 1 am and 5 am). For this a second location matrix had to be populated with night-time parking frequencies using the same method as the overall locational matrix, but only examining location data referring to times between 1 am and 5 am.

The second criterion was included in the definition of "Home" to address multi-house families (vacation homes, driving teens with divorced parents, couples not yet living together, college students, etc), as well as cars that were sold or households that moved during the study. For those vehicles that had more than one “Home” location, parking at any of them is counted as parking at “Home”. The timespan of 1 am to 5 am for the second criterion was selected to correspond to the period of minimal vehicle use. The numbers of cumulative nighttime hours was selected to give results most nearly consistent with NHTS survey data (USDOT-BTS 2003a): When much less than 100 nighttime hours was used to define additional “Home” locations, the fraction of vehicles parked at home through the night dropped; when much more than 100 hours were required, the fraction of vehicles found to be parked at “Work” (defined below) during workdays fell significantly.

4.3.2 Work Locations

The location where each vehicle spent the next most hours during the year, excluding a 50 meter radius around “Home” locations, was labeled “Work”. Subsequent parking pattern analysis (discussed with Figure 2) suggests that in most cases, the labels “Home” and “Work” accurately reflect the activities at those parking locations. These labels may be incorrect for some cases night shift workers, those working predominantly from home, those with non-stationary jobs (contractors, travelling sales), etc. Nevertheless, as these data are used to model placement of EVSEs at these locations, drivers would still have an EVSE in the most frequented parking locations. In addition, it is hoped that even collectively, such individuals are scarce among the population, so their impact on aggregated and averaged results is small (Bureau of

Labor Statistics 2002). With this clarification, the words "Home" and "Work" will be used subsequently to refer to these two locations.

4.3.3 Basic Findings and Method Validation

A very general metric of the utility that plug-in vehicles could provide to the grid is the amount of time during the year that they would be plugged in. This potential will be evaluated in greater detail in subsequent chapters, but the evaluation of this parameter also serves as a validation of the assumptions and methods outlined in this section for the identification of home and work locations. The most basic form of this analysis is to simply evaluate what fraction of the time vehicles spend parked at 'Home', and at 'Work', and compare that to general knowledge and previous research about how vehicles are used, the workforce, and other factors.

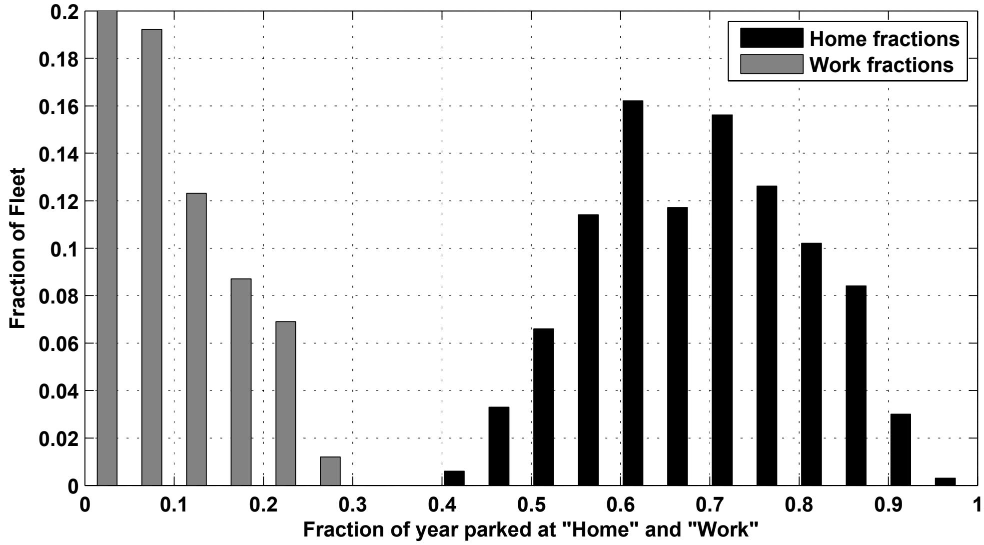

Figure 1: Distribution of time spent parked at Work (grey bars) and time parked at Home (black bars). The leftmost work bar is truncated from its true height of 0.52.

The histograms in Figure 1 shows the distribution of time spent parked at Home and at Work. For each vehicle, the interpreted fraction of time has been normalized by the number of days that vehicle was under observation. For example, the tallest black bar in Figure 1 indicates that about 16% of vehicles spend between 60 and 65% of the time parked at Home. More broadly, a large majority of the fleet (68%) spends between 55% and 80% of the time parked at Home. The mean time parked at Home is 70%. This finding agrees with a general analysis of vehicle use. A commuting vehicle, for example, may leave the house at 8:30am and returns at 5:30pm on work-days, and spends on average 3 hours away from home each day of weekends, holidays, and (two weeks of) vacation. Such a vehicle would be spending 71% of the year at home, right at the mean of the sample of vehicles shown in Figure 1.

The grey bars on the left of Figure 1 indicate the distribution of time parked at Work. A typical full time job in the U.S. requires spending just under 2000 hours at work, which corresponds to just less than 22% of the hours in the year. We therefore expect the number of vehicles parked at a work location more than 22% of the time should be small, which Figure 1 shows to be the case for the definition of 'Work' used. It is interesting to note that the majority of cars spend a substantially smaller amount of time at their respective second most common parking locations, and the tallest 'Work' bar, which represents vehicles that spend less than 36 hours per month at 'Work', has a value of 52% (the figure was cropped for clarity). This finding is also consistent with external data, and can be compared to the NHTS result stating that only 27% of trips are to or from work (Santos et al. 2011), and the fact that there are more vehicles in America than there are full-time jobs, so many cars must rarely if ever park at a full time workplace. The mean value of time spent parked at the second most parked-at location, "Work", is 8%, the median is 5%.

The distribution of vehicles parked at Home and at Work can also be assessed as a function of time of day. For this, the year was once again divided into a series of points in time 10 minute apart (12:00, 12:10, 12:20 etc.), and at each point in time the cars parked at each location were counted. These totals were then normalized by the number of cars in the study through time, and then separated into workdays versus weekend or holidays. (This delineation required a certain amount of interpretation, since several federal holidays exhibited parking patterns characteristic of work days. These are Martin Luther King Jr. Day on Jan 19th, 2004, President's Day on Feb 16th, Columbus Day on Oct 11th, and Veterans'' Day on Nov 11th. On the other hand, one non-holiday, the day after thanksgiving, Nov 26th 2004, exhibited parking patterns characteristic of holidays). Thus for each 10-minute time-span and each location, there is a distribution of fractions of the fleet parked there. In Figure 2, these distributions are characterized by their mean, maximum, minimum, and standard deviation, separately for Home and Work.

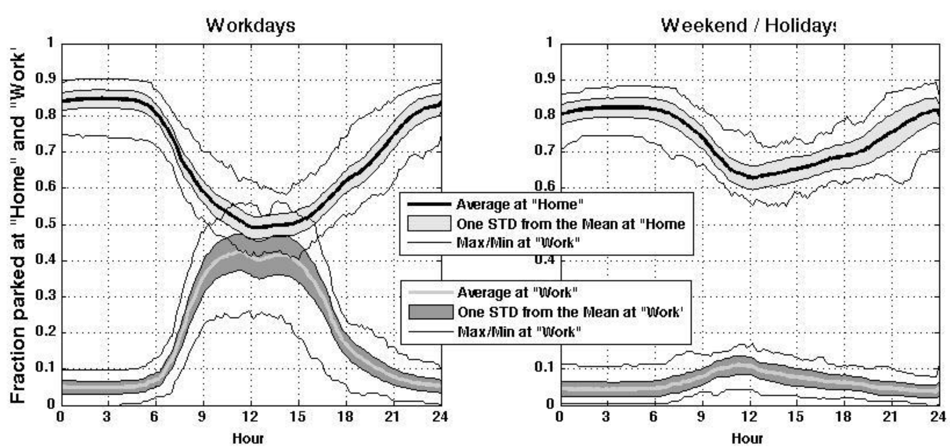

Figure 2: Fraction of fleet parked at "Home" and "Work" through time on workdays (left plot) and on weekends and holidays (right plot).

Figure 2 shows that the fraction of the fleet at Home is at its maximum and nearly constant from midnight through about 5am on workdays. On weekends and holidays, by contrast, some vehicles get Home a bit later at night and stay at Home a little later in the mornings. On workdays (left plot), about 35% of the fleet leaves Home and arrives at Work between about 5 am and 11 am. The fraction at work overnight never drops below 3.5%, corresponding to Labor statistics on night shift work (Bureau of Labor Statistics 2002). This analysis also shows roughly 40% of the fleet is at Work on weekdays, roughly 1/10th of those (~4% of the fleet) leave Work at lunchtime, and the population at Work declines steadily between about 3 pm and 5 pm, more slowly from 5 pm to about 9 pm, and those remaining continue to depart, slower still, after 9 pm. On weekends, the fraction of the fleet at Work increases by about 8%, up to about 12% for a couple of hours in the morning, then tapers steadily down to the overnight rate by about 9 pm.

These first two figures serve two roles. One is as a diagnostic analysis of the characterization of home and work parking locations, the other as definitional and descriptive of ratios and changes in parking patterns. In their first role, Figure 1 and Figure 2 suggest that the categorization of Home and Work locations for most cars are reasonable, corroborated by the correspondence of these results with Labor statistics and general knowledge of travel patterns.

Giving the locations identified by this method the names “Home” and “Work” is somewhat speculative, however the identification of the first and second most-used parking-locations is nonetheless relevant to the design and utility of charging infrastructure. Even if the most parked at location is not home, it is still the location at which an EVSE will do the most good, and the location on which groups interested in EVSE deployment should focus. And the second-most parked-at location may be useful for extending the range of vehicles, whether or not it is where the vehicle's owner works. A full characterization of these locations is beyond the scope of this work, as it will require extended access to the raw data and correlation between that dataset and geographic data.

4.4 Vehicle Behavior upon Plugging In.

The availability of charging infrastructure is not the only thing that will determine whether a vehicle charges or not at the conclusion of a trip. There also can be incentives or other mechanisms designed to encourage charging behavior to accommodate the needs of the grid. Possible effects of these mechanisms will be included in the modeled behavior of vehicles in the form of a variety of charging algorithms.

Eleven charging algorithms have been devised that differ in when the battery may be charged, how fast it may be charged (*i.e.* maximum charging power limited to less than infrastructure capacity), and the target state of charge.The algorithms can be grouped into four sets based the information used to control charging rate. The first 'set' consists of only one algorithm, 'dumb charging', which uses neither predictive nor driving nor time-of-day information, but simply charges when plugged in and continues charging until the battery is full. The second set uses only the time of day as a rough estimate of information about the needs of the electrical grid, mimicking time-of-use rates and their potential effects on vehicle owner behavior, while possibly under-representing actions vehicle owners could take to prepare for their own travel needs. The third and forth sets use both the time of day and information about the driving habits and upcoming travel needs of the vehicle owner, which may better reflect the actual interplay of vehicle owners with incentive structures and their own concerns about trip success. This effect has been witnessed by studies of new EV drivers who may go several days without charging if upcoming travel needs are modest and within the range to the remaining charge at day's end. A more complete description of the charging algorithms used is presented in the analysis of their respective grid impacts, in Chapter 8.

4.5 Model Description

This research relies on a transportation and energy model that simulates a fleet of electric vehicles operating on the driving patterns and schedules revealed by the data described in section 4.1. As laid out in the preceding sections, this research effort is principally focused on the ability of EVs to replace existing gasoline vehicles, and the dangers or potential benefits of having manageable loads with storage plugged into the electric grid. The model operates by building numerous permutations of a test fleet of electric vehicles, wherein each permutation is a unique combination of the four variables under investigation (battery size, charging rate, charging infrastructure buildout, and charging algorithm). This test fleet is then set to the task of mimicking the driving patterns of conventional vehicles documented in the study from Georgia Tech.

The year is segmented into 10-minute time spans, and various output variables are initialized for each vehicle, for each time segment (52,704 segments per year). The most important of these being the battery state of charge, measured in kWh, and the grid load due to the fleet, measured in kW. Beginning with a full battery in the first segment of the year, for each subsequent segment the amount of energy contained in each vehicle's battery is adjusted based on distance traveled or on whether a vehicle was charging. When a vehicle has been driving for the preceding 10-minute segment, the energy stored in its batteries is depleted according to the distance traveled and the generic small vehicle efficiency developed in section 2.4. When no driving has taken place in the preceding 10-minute segment, the parked vehicle may ether charge or not charge depending on the charging infrastructure and charging algorithm being applied to that permutation of the test. When the vehicle has been charging in the preceding segment, the battery energy is increased corresponding to the charging power, and the fleet grid loading is likewise increased. This procedure is repeated for each of the vehicles in the dataset to generate fleet total or fleet average conditions and results for that scenario.

If during a drive the battery energy is fully depleted, then an instance of failing to replicate known driving patterns, or 'trip failures', is recorded for that specific vehicle, for that specific scenario, at that specific 10-minute time segment. When the vehicle is parked at a plug, additional variables are also indexed to reflect the potential of the vehicle to provide grid services at that point in time. As each of the four input variables is adjusted, a new scenario and thus a new set of charging loads, battery state of charge and trip failure variables, is generated. By comparing one scenario to another, based on variations of one (or more) of the variables, the effects of that variable can be isolated and quantified.

In summary, when a vehicle is travelling, its interaction with society is limited to transportation services, and is of little concern to the electric system. When the travel is concluded, however, a plug-in vehicle can interact with the grid in one of a variety of ways. If the vehicle is not plugged in, it is not attached to the grid, and will have no interaction at all. If the vehicle is plugged in and draws energy from the grid either by default or by design to provide for upcoming travel, it is a load to the electrical energy system. If, on the other hand, the vehicle concludes a trip, has no upcoming travel or has enough energy onboard for that travel, then it could provide grid services, limited by the power capacity of its connection to the grid and its ability to communicate, until such time that a charge is required for the next departure.

The result of this modeling effort thus a database of variables, distributed throughout the fleet, from which a description of the effects of these possible interactions between plug-in vehicles and the electric grid can be extracted. From the recorded variables a variety of relevant metrics can be generated, generally with further processing and amalgamation such as that described for parking locations.

Chapter 5

DAILY VEHICLE USE PATTERNS AND TRAVEL ADAPTATION FOR EV DRIVERS[17]

A simplified travel model is presented here, based on the data described in Chapter 4 but using only daily travel distance rather than separating trips during a day. By looking only at the sum of daily travel rather than discrete trips, this analysis in effect makes three assumptions about the charging of these vehicles. First, it implicitly assumes that vehicle will always be charged overnight. Secondly (and correspondingly) it assumes that vehicles will only be charged overnight, thus that no charging will take place during the day between trips, regardless of vehicle location. Finally, it assumes that each vehicle's batteries will always be full every morning. (In Chapter 6, the analysis will be re-done with these assumptions removed, relying instead on an analysis of vehicle location to determine whether charging can be performed when the vehicle is stopped during the day.)

In section 5.1, a brief introductory overview is given for the travel model, and the variations in vehicle utilization within the data are described. Section 5.2 begins the significant results with several summary statistics of each vehicle's maximum daily

17 This chapter is drawn from a published paper on which I am lead author, Pearre *et al.* (Pearre et al. 2011), including large blocks of text used verbatim. Figures are cited individually as being from that article, but text blocks are not.

mileage. Section 5.3 introduces a novel metric (first introduced by Pearre *et al.* (Pearre et al. 2011) for EV substitutability—days requiring adaptation. In Section 5.4 the vehicle population is subsampled in order to characterize the variability within the fleet. Finally, in section 5.5 the significance of daily range analysis and the results are discussed.

5.1 The 'Daily Driving' Model and Data Characterization

By viewing each day as a single travel event, the daily driving analysis presented in this chapter removes from consideration any potential charging infrastructure availability as well as the effects of faster or slower battery charging rates; only overnight charging, and charging to full each morning are permitted, and are assumed to occur in all cases. Nevertheless, it preserves a great deal of information about the variability in range needs among the population of vehicles, and between days for individual drivers.

In characterizing the variability in each individual driver's daily travel range, the results of an EV substitutibility analysis allows the computation of the vehicle range necessary to accommodate the driving of a given segment of the population. It also enables calculating the fraction of days on which each vehicle's driving falls within a given range. This later characterization leads to the concept of "adaptation days", which is defined as the number of days any given driver would need to adapt his or her travel patterns if constrained by an electric vehicle with a range lower than her maximum liquid-fuel-vehicle travel range on any single day.

Adaptations could mean, that vehicle drivers recharge during the day, borrow a liquid-fueled vehicle, or save some errands (and the associated trips) for another day. This analysis finds that the distribution of miles traveled per day is positively skewed, with a "long tail" on the high mileage side (i.e. the frequencies of miles/day drop off quickly above the average, but the maximum daily range can be many times the average, this will be shown in Figure 3). This means that an individual driver's range requirement for all trips in the year is much greater than her range requirement for 'almost all' days in the year. As a consequence, if some number of "adaptation days" is factored into vehicle use, the substitutability of EVs increases dramatically.

5.1.1 Daily Travel Distance Distribution

Within the study, 470 of the 484 vehicles were monitored for more than 50 days. I used 50 as a minimum number for this analysis, those with fewer valid days were discarded. For each of these 470 vehicles, daily driving distances were grouped into 4-mile bins (days with 0 – 4 miles of travel, days with 4 – 8 miles of travel, etc.), and the resulting bin frequencies were normalized by the amount of time each vehicle participated in the study. The distributions were then averaged to compute the daily distance distribution for the 148,350 driving days of the entire fleet, shown as a histogram in Figure 3. Days with no driving at all, which were very frequent, are not shown.

The left-most bar in Figure 3, for example, indicates that on average a vehicle is driven between 0 and 4 miles about 15 days in the year. The histogram in Figure 3 shows that the vast majority of daily range need is in the 0 to 50 mile range. Excluding days of zero driving, the mean daily driving range is 44.7 miles and the median is 29.9 miles. When days with no driving are included, the mean is 32.6, and the median is 18. The survey-based NHTS data give a mean value of 29.1 miles nationwide, again illustrating that this sample from Atlanta, with a mean of 32.6 miles, has a slightly higher daily driving range than the US average.The mode, the most common daily distance range, is 12 - 16 miles, the highest bar on the histogram of Figure 3, though this range changes slightly if different bin edges are selected.

A separate solid line in Figure 3 shows the number of days a given mileage is exceeded. It is calculated as the sum of all day counts (all histogram bars) to the right of any given mileage.

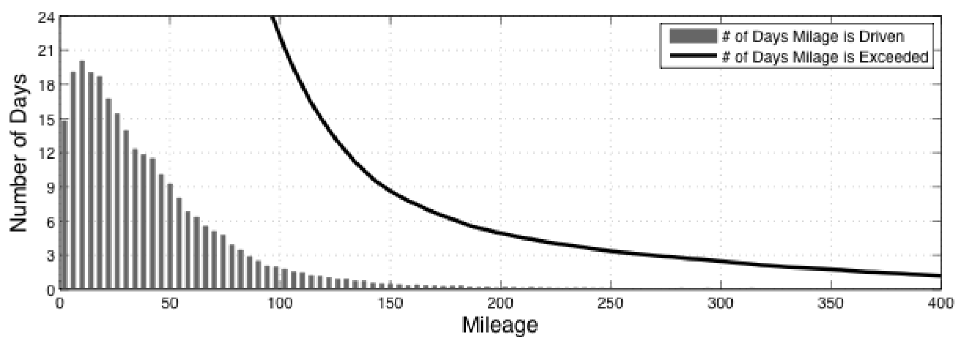

Figure 3: Average Daily Mileage Distribution. Histogram of daily mileage during 148,350 driving days over a year. Grey bars show 4 miles/day bins. Days when cars were not used at all are not tabulated in the histogram. The black line shows the number of days per year that each mileage is exceeded. From Pearre *et al.* (Pearre et al. 2011)

Figure 3 shows, for example, that on the vast majority of days, daily driving distance is below 100 miles. The solid black line shows that 100 miles or more of daily driving occurs on average only 23 days in the year (this works out to exceeding 100 miles in a day, on average, once every 16 days). This finding is within the 95% confidence interval (2.55%) of Gonder *et al.* (Gonder et al. 2007), that found less than 5% of daily driving (18 days of 366) exceeds 100 miles. Similarly, the figure shows that 150 miles or more of driving is rare, occurring on average fewer than 9 times in the year (about once every 6 weeks). This agrees with the finding that long distance travel by automobile is a fairly rare event in this sample of households (Xu et al. 2009). As another comparison, the relative frequencies of exceeding of 70, 150, and 200 miles within one day in Figure 3 is of particular interest because mass-produced electric vehicles with 70 miles range, such as the Nissan Leaf (Nissan Motors 2009) have been on the market for a couple of years at the time of writing, and vehicles with 150 and 200 miles of range or more (Tesla 2013) are already available in smaller quantities at higher cost.

The average vehicle in the study is not driven at all on more than a quarter (27%) of individual days, thus if zero daily range were not excluded from Figure 1, zero miles per day would be the mode with, on average, 99 instances per year. In the Atlanta study, the goal was to instrument all household vehicles driven more than 3000 miles per year. Hence, the sample included the primary commute vehicle, secondary service vehicles, etc., but any vehicles in minimal use at the time the study was launched was to have been excluded. Other research on transportation options in Atlanta has shown that few of the households participating in the study had a viable commute option by bus or rail (Zuehlke 2007), so few zero-range days in this sample are likely to be due to commuting by transit. However, regular automobile commuters are occasionally ill or elect to work at home, or may carpool or get a ride from another member of the household and thus not use secondary vehicles on many days. In addition, the data include weekend days and holidays, when one primary vehicle is typically shared by the household and secondary vehicles sit idle. Because zero daily mileage is so common, it was omitted from the graph in Figure 3; were it included, the scale would be expanded so much as to render unreadable the distinctions within 0 to 24 days.

The dark line in Figure 3 can be thought of as addressing the question; "How many days per year would the average driver have to adapt his behavior by, for instance; 1) switching to a gasoline car, 2) charging during the day, or by 3) planning the day's trips to cover less total distance?" Thus, re-phrasing the prior observation of the intersection of the line at 150 miles, from Figure 3 we would conclude that an electric vehicle with 150-mile range, and no recharging during the day, would meet the unmodified driving need of the average driver all but 9 days in the year. It is important to note that the data include days in which the household is conducting long distance tours. If we assume that electric vehicles would not likely be used for long distance travel (i.e. a gasoline vehicle would be rented or a secondary household vehicle would be employed), limited range electric vehicles would be inadequate on an even smaller number of days.

This initial graph will be refined in the following sections by examining distributions among drivers and among trips, and in subsequent chapters by examining charging during the day and other forms of adaptation. As an initial analysis Figure 3 is still of value in illustrating the basic distribution of daily driving distances across all cars in the sample.

5.1.2 Days of Vehicle Use

The analysis presented in this section compares how many days each vehicle is used with the daily distance that vehicle is driven. As in section 5.1.1, the fleet was again limited to the 470 vehicles observed 50 days or more, and as before results were normalized by the amount of time each vehicle was under observation. In this analysis, each vehicle is characterized by two parameters: the number of days on which that vehicle was used during the year and the average mileage driven on those days when it was used. As an example, if a vehicle was in the study for 100 days, and driven 20 miles on day 1 and left unused on the remaining 99, then the average daily usage would be 20 miles.

Figure 4 is, like Figure 3, a graph of the 470 vehicles. Here, vehicles are arbitrarily grouped into subsets of 30.5 normalized days, thus 12 groups are shown for the year (the first subset is used between 0 and 30.5 days during the year, the second between

30.5 and 61, etc.). In the top plot of Figure 4, for each subset, the sample mean daily mileage is indicated with a square marker, and 95% confidence limits of the mean, a function of both the sample variability and the sample size, are indicated with error bars. In the bottom graph of Figure 4, the population of each subset is shown, as a percentage of the 470 vehicles.

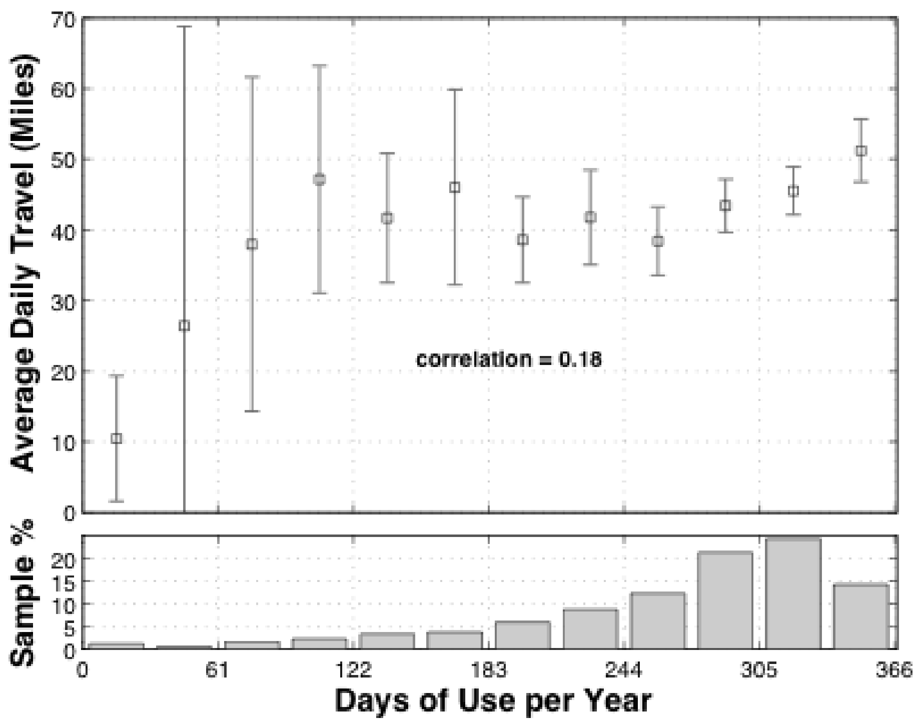

Figure 4: Daily Travel in Miles vs. Days of Vehicle Use. Vehicles are divided into 12 subsets, by normalized days of use in the year. Top: Average daily mileage on the days they are driven for each subset. Squares indicate the sample mean values for each subset, error bars indicate 95% confidence limits in the mean. Bottom: Subset population, given as a percentage of the 470 vehicles examined.From Pearre *et al.* (Pearre et al. 2011)

Figure 4 reveals that there is little relationship between the frequency of use of a vehicle and its average daily miles of travel. The correlation coefficient (r) between these variables, calculated using the disaggregated data, is 0.18. The least used vehicles in the sample, vehicles that are used fewer than 30.5 days per year or about every 12 days or less, on average travel only 10 miles per day when they are used. Excepting this lowest group, there is little variation in average daily travel (the square boxes in the top graph of Figure 4) between the least-frequently used and most-frequently used cars. The low r coefficient shows that there is only a very weak linear relationship between how many days a vehicle is driven, and how far it is driven on those days.

The finding that frequency of use is not strongly related to distance per day motivates further analysis in that it indicates the existence of a population of vehicles that are used frequently, yet that on average drive short distances relative to national average driving patterns. This population could be one early target market for EV sales, because for these households, a limited-range vehicle could be their primary vehicle, in daily or near-daily use.

5.2 Maximum Daily Travel Distance

The next analysis is similar to that presented in section 5.1.1, but tabulates only one day of the year for each vehicle; the day in the year on which that vehicle was driven the greatest single-day distance. The analysis gives an indication of the "worst case" for limited range EVs, a situation important to understand for households who might have no alternatives to their EV. Due to the importance of statistical outliers to this analysis, we have restricted it to vehicles that participated in the study at least 75% of the year (274.5 days out of 366). If the fleet driving distance distribution found in Figure 3 can be extrapolated to individual vehicles, the mileage on the worst of 50 studied days would only be 46% that of the mileage on the worst of 366 studied days. In contrast, the mileage on the worst of 274.5 studied days would be 93% of the mileage on the worst of 366. This reduces the sample to 363 vehicles.

In Figure 5, the distribution of maximum daily mileage for the 363 vehicles is shown as a histogram with bin sizes of 50 miles. No adjustments have been made for vehicles with less than a full year of data. The vehicles characterized here were in the study an average of 357 days, so any bias from missing data should be small. Note that, unlike the all-data histogram of daily driving in Figure 3, the distribution of the fleet's maximum travel in Figure 5 shows at least 2% of the fleet in each bin from zero to 700 miles. Few cars exceed a daily travel maximum of 650 miles, which corresponds to 10 hours spent driving at an average speed of 65 mph. Only four vehicles (1.1%) exceed 1,000 miles, none exceeds 1400 miles, which would require averaging 70 mph for 20 hours. The diminution of driving from 650 – 1000 miles can be interpreted as a physical limit imposed by road speed limits and human exhaustion. The mean value in this distribution is 355 miles, and the median is 312 miles. To match EV design to the usage in Figure 5 is arguably an overly severe test for electric vehicles, as most of these trips are long distance trips outside of the region, for which most households could select or rent an alternative vehicle.

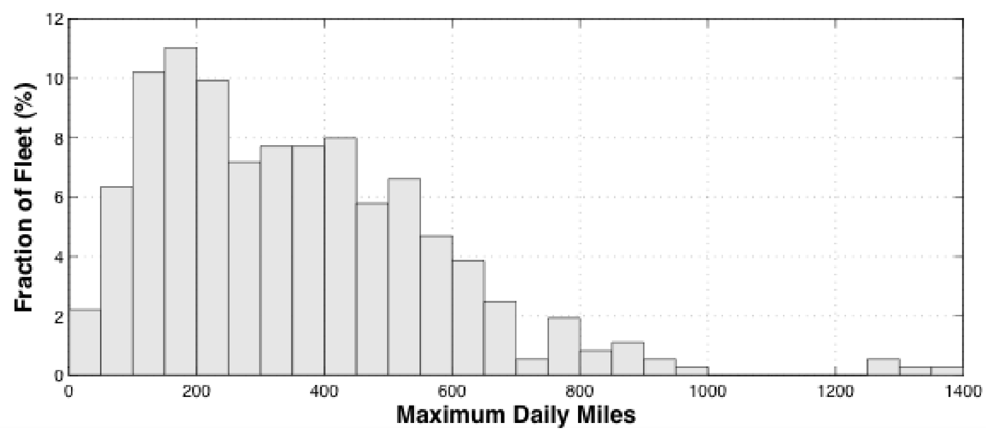

Figure 5: Maximum Daily Mileage Distribution. For each of the 363 vehicles, the day of maximum travel distance is identified, and that day's distance is tabulated and sorted into 50-mile bins. From Pearre *et al.* (Pearre et al. 2011)

Figure 6 is the cumulative distribution of the maximum daily mileage for the same 363 vehicles. The cumulative distribution for a given value of daily driving distance, is defined to be the fraction of the fleet that never exceeds that distance in the study year. This is the inverse definition from that used for the exceedance fraction shown in Figure 3. Note that due to the very long distances covered in one day by a small number of the vehicles in the sample, the x-axis of Figure 6 has been made logarithmic so that those long distances could be captured, without loosing resolution at shorter maximum travel values that may be of more interest to the discussion of EV or PHEV design.

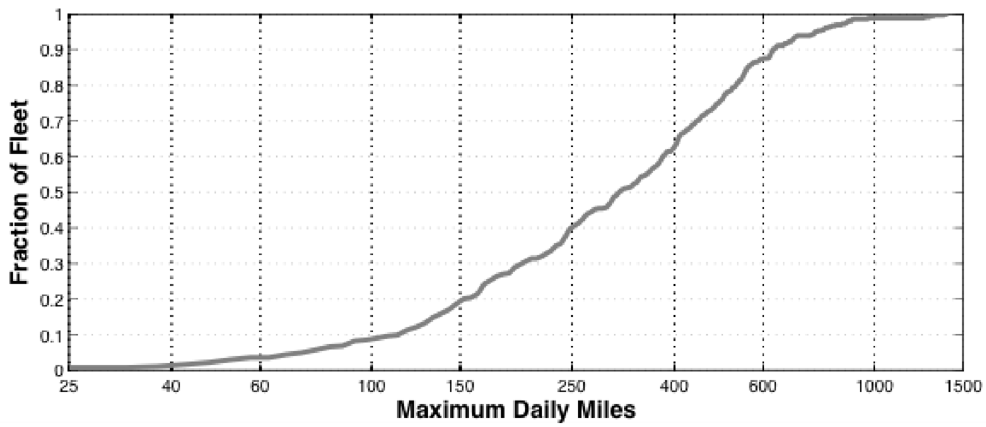

Figure 6: Maximum Daily Mileage CDF. The cumulative distribution function of each of the 363 vehicles' maximum daily driving distance over a year. For each value of distance on the x-axis, the curve indicates the fraction of the fleet that never travels more than that distance during the year.From Pearre *et al.* (Pearre et al. 2011)

As can be seen from the exceedance curve in Figure 6, an electric vehicle with a range of 100 miles, charged only once per day at home, overnight, could substitute for 9% of the fleet. Conversely, for the remaining 91% of the fleet, that same 100 mile EV would have failed to address the driver’s range needs on at least one day during the year. Similarly, looking at the 50% mark on the y-axis, an EV would require 313 miles of range to fully substitute for half of the vehicle fleet. Again, by “fully substitute” we mean that for 9% and 50% of drivers, an electric vehicle with 100 and 313 miles range, respectively, would satisfy all driving needs, every day of the year, with no change from their gasoline vehicle habits. It should again be noted that this is a stringent test, as it includes vacation driving and other long trips for which vehicle substitution might be expected.

5.3 Days Requiring Adaptation

The previous analyses examined the distance travelled and the number of days each vehicle was used. Drivers who never exceed a given range in a day are potential users of limited range vehicles without adaptation. In this section, the data are analyzed based on the notion that a driver might be willing to adapt his or her driving behavior on some number of days. By “adapt driving behavior” we mean either 1) substituting a liquid fuel vehicle (use another car in the household or rent a gasoline car), 2) recharging during the day or en route, 3) delaying part of the travel until the next day (e.g. instead of 3 side errands after work, two are done one day and the third the next day), or 4) choosing a different mode of transport (commuter rail, bus, aircraft, bicycle etc). Even though vehicle sharing within a household might be seen as so simple as not to qualify as an “adaptation”, we include it in order to tabulate without judgment all changes required to adapt to limited range.

The need for adaptation is assessed in terms of three factors: Given a vehicle with **X miles** of range, **Z%** of the study drivers would find that vehicle fully satisfies their current driving patterns on all but **Ydays** of the year. On those Y days, they have to make some form of adaptation, as itemized above. In these terms, the previous analyses for Figure 5 and Figure 6 set Y to zero. In the following analysis, the implication is that a vehicle driver might be willing to adapt a few days a year for the benefits of owning and living with an EV.

The information needed to answer this question is a three-dimensional surface. In Figure 7 below, “Vehicle Range” (x-axis) is the distance a given EV can travel in a day, “Days Requiring Adaptation” (y-axis) is the number of times during the year that that range would not be sufficient, so the driver would have to adapt by one of the four methods above. The isographic lines (which map the surface or Z-axis) then describe the fraction of the fleet that would require adaptation on this number of days. Because this analysis, like that in section 5.2, is susceptible to statistical outliers, we again use only the 363 vehicles monitored at least 274.5 days during the year. In addition, the failure rates have again been normalized to failures per year based on the length of time each car was in the study, so the y-axis is correspondingly “Days Requiring Adaptation” per year.

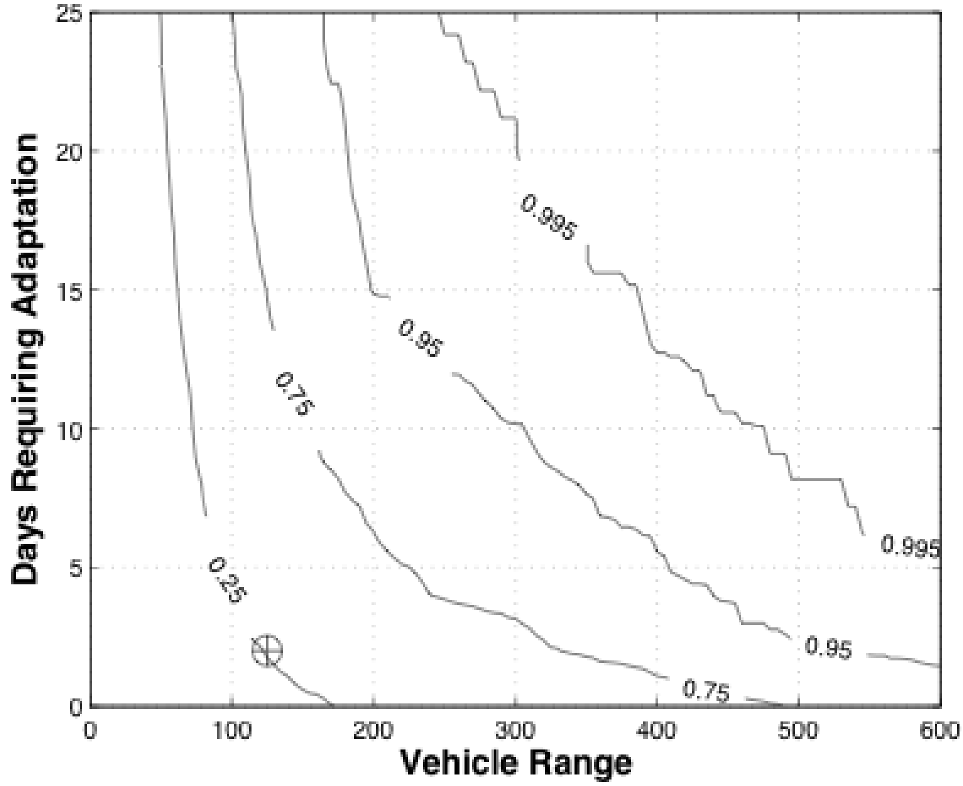

Figure 7: Driving Success Surface. The fraction of the 363 vehicle fleet (numbers on lines) which would be suitable for an EV with the shown vehicle range (x-axis), on all but a given number of days requiring adaptation (y-axis). From Pearre *et al.* (Pearre et al. 2011)

To help interpret Figure 7, a "crosshair" (the cross and circle target) has been included near the lower left-hand corner. On the "Vehicle Range" axis, the crosshair is aligned with 125 miles, and on the "Days Requiring Adaptation" axis the crosshair is aligned with 2 days. Aligned on the axes in this way, the crosshair falls on the 0.25 line. This may be interpreted as follows: If an electric vehicle has a range of 125 miles, and the owners of these vehicles are willing to adapt their travel behavior on two days per year (e.g., switching vehicles or charging during the day), then that vehicle would be compatible with the current driving patterns of 25% of current gasoline vehicle drivers. In other words, 25% of the monitored vehicles traveled no more than 125 miles per day, except on two or fewer days per year.

As another example using Figure 7, three quarters of drivers (75%) could substitute an EV with 155 miles range for their current gasoline-fueled vehicles if they made some adaptation to limited range on 10 days per year. (Again, with "adaptation" meaning using a second household vehicle, renting, stopping to charge en route, etc. on those 10 days)

Looking at the effect of each axis in Figure 7, as the EV battery range increases (moving to the right), as is to be expected the fraction of drivers whose travel patterns can be accommodated increases. Considering the y-axis, if drivers are willing to accept more days of adaptation (moving upward), the fraction that could life with a vehicle with that range likewise increases (and vice-versa with smaller batteries and lower driver tolerance for making adaptation).

Figure 8 shows another view of the data surface in Figure 7. Figure 8 moves the fleet fraction values to the y-axis and picks four representative numbers of days of adaptation to describe the surface. The four lines represent zero, two, six, and 25 days of required adaptation. The "No adjustment days" line depicts the same information as the cumulative distribution function in Figure 6, though the axes scale has changed. In Figure 8, the intersection of the position on the x-axis corresponding to 125 miles of range, and the position on the y-axis corresponding to one quarter of the fleet (0.25) lies on the light dotted line, indicating they would have to tolerate 2 adaptations per year. These are the same conditions used for the cross-hairs example in Figure 7.

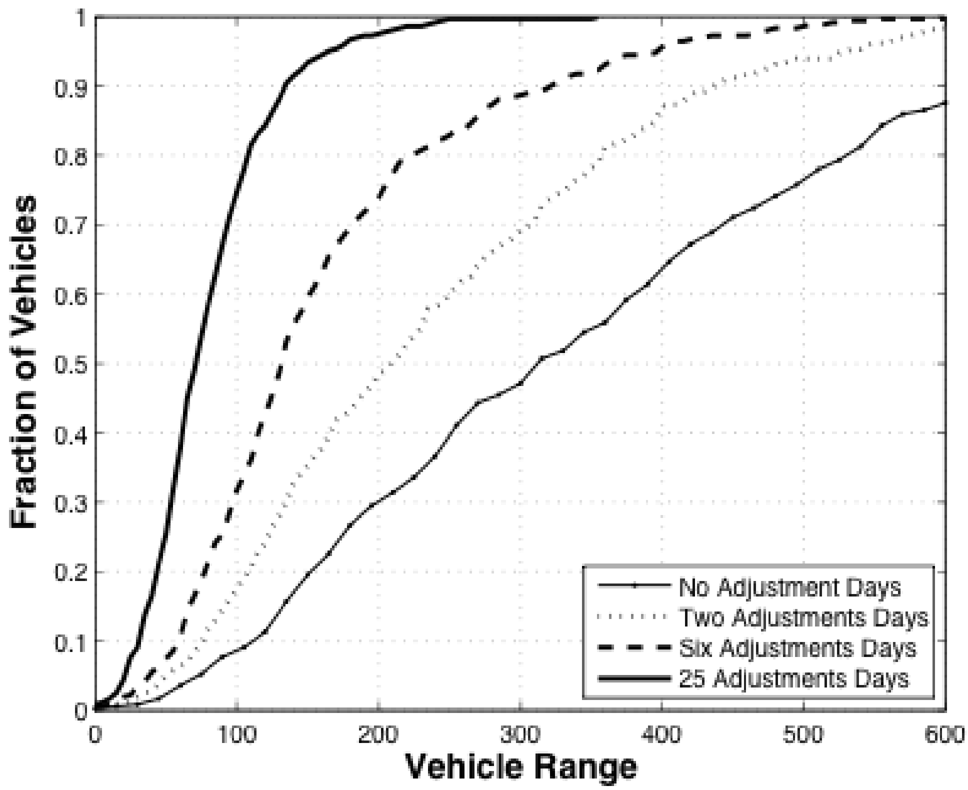

Figure 8: Driving Success Surface, by Adaptation Days. Fraction of the 363 vehicle fleet appropriate for varying vehicle ranges, with the four lines representing vehicle owners willing to make adaptations 0, 2, 6, and 25 days in the year.From Pearre *et al.* (Pearre et al. 2011)

The analysis presented in the previous section showed that EVs with 100 miles range could replace about 9% of all cars with zero driver adaptations. Figure 8 shows that, if the drivers were willing to adapt on 2 days per year, those 100-mile EVs would meet the travel needs of 17% of drivers. Or, if owners were willing to adapt six days per year, the same 100-mile EV would meet the needs of 32% of drivers.

5.4 Segmenting by Average Daily Driving Distance

We have found that a substantial fraction of vehicles travel few miles on those days when they are driven, largely independently of how many days they are used (Figure 4). We now segment the data into four groups, based on their average daily driving distance. The use of four groups was guided by the desire to keep the group size large (suggesting fewer divisions), yet focus on the group with smallest range needs (suggesting a small first group, or more divisions). Daily driving distance is again defined by summing the mileage of all trips started on each day, and taking the average mileage of those days, excluding from the calculation days when no trips were made. This method provides simple market segmentation by driving distance, where people who drive the shortest daily distances may be the most suitable buyers of limited-range EVs. This group, if they are aware of their own range needs, may be more likely to seek to buy an EV. (Other attributes of buyers, such as willingness to pay the cost of the vehicle and cost per mile, would be included in a more complete market segmentation, but those would require very different data and analysis, and are not included in the present analysis of driving range needs.)

In Figure 9, the distribution of daily miles traveled is shown for each of the four groups. The one-quarter of vehicles with the lowest daily mileage is shown by the darkest line. Note that each group is one-fourth of the vehicle fleet, thus the number of vehicles represented by each line is reduced from the total of N = 363 used in previous analyses to this group's of N = 91.

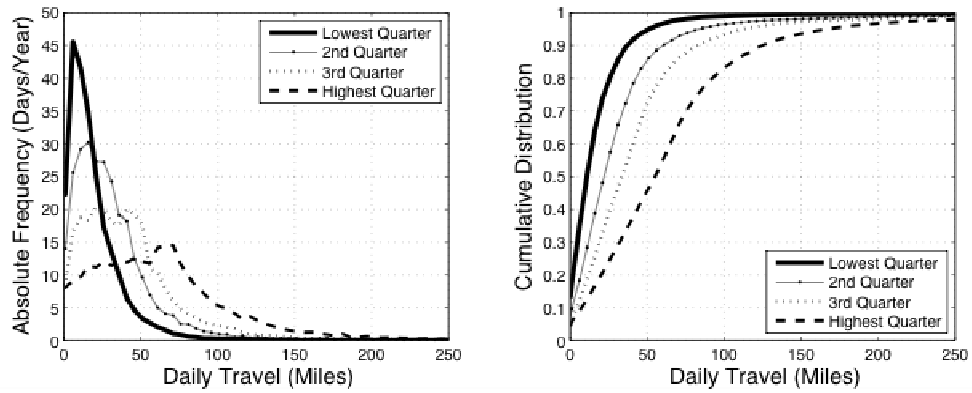

Figure 9: Trip Length Distribution by Sub-group. The absolute (left graph) and cumulative (right graph) frequencies of daily distance travelled, for four sub-groups, selected by their average daily distance driven.From Pearre *et al.* (Pearre et al. 2011)

Figure 9 (left graph) shows that an EV designed with 150 mile range would satisfy nearly all driving requirements of three-quarters, that is, all but the highest-mileage quarter of the vehicles (dashed line). Or, referring to the right graph in Figure 9, to satisfy 95% of the days of driving requires only a 56-mile range for the lowest-traveling quarter, a 86 mile range for the second group, a 116-mile range for the third group, and a 171-mile range for the highest-mileage quarter.

Next we pick only the lowest-mileage group of 91 vehicles to examine more closely. The rationale for looking at this group more carefully is that they are the quarter of the population most likely to find that EVs with limited range have little impact on their driving needs. This group corresponds to the solid black lines in Figure 9. In Figure 10, the graphs from Figures 7 and 8 are repeated for only these low daily mileage vehicles. Note that the maximum displayed mileage (x-axis) was 600 miles in figures 7 and 8, but has been reduced to 250 miles in Figure 10, for higher resolution and corresponding to the low prevalence of very high mileage days.

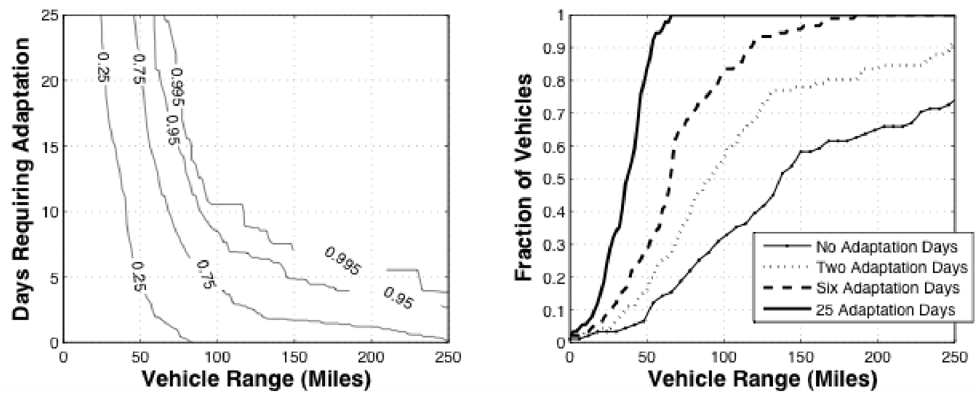

Figure 10: Driving Success Surface for the 91 vehicles with the lowest average daily travel. The fraction of the fleet surface (left plot), and travel adaptations needed (right plot) are shown as a function of vehicle range. See captions for Figures 7 and 8.From Pearre *et al.* (Pearre et al. 2011)

For the lowest travel distance quarter of vehicles, the results presented in Figure 10 show that an EV with a 100-mile range would be sufficient for 32% of these drivers, without requiring any adaptation (compared to 9% of the whole fleet). If two days per year of adaptations are tolerable, the 100-mile EV could satisfy 56% of these drivers (compared to 17% of the whole fleet). And if these drivers were willing to adapt their behavior six days per year (the dashed line), 83% of those drivers could replace their cars with a 100-mile range EV (compared to 32% of the whole sample).

5.5 Discussion of Daily Range Analysis

In sum, this empirical investigation of daily range needs, based on actual driving behavior of almost 500 vehicles over a full year, makes clear that limited range EVs can meet the needs of a large proportion of drivers. Nine percent of vehicles do not exceeded 100 miles in any one day in the study year. For drivers who are willing and able to make adaptations on a few days a year, the fraction of the population for whom the substitution of an EV for a conventional gasoline car is larger: If they are willing to make adaptations on 2 days a year, the same 100 mile range EV would meet the needs of 17% of drivers, and if they are willing to do so 6 times a year, just once every other month, limited range vehicles would work for 32% of drivers.

The suggested adaptations in driving behavior are reasonable for a large percentage of the population. In the United States, for example, the average household owns 1.9 vehicles, and 66.4% of households owned two or more vehicles at roughly the time this travel data was collected (USDOT-BTS 2003a). In these multi-car households, when trips outside the range of the EV are to be taken, “adaptation” as discussed in our analysis, would be a simple matter of taking a different vehicle already in the household. On long road-trips such as vacations, a common cause of extreme daily mileage, the family is likely already choosing a longer-range and higher carrying capacity vehicle when one is available within the household. A more thorough investigation of intra-household vehicle substitution as a mechanism of travel adaptation is presented in section 7.4.

This research consisted of an analysis of the distance driven daily, but actual vehicle design would need to leave some margin of surplus range over the needed driving. This is to prevent an error or an unplanned side trip from stranding the driver, and to avoid driving with little energy remaining in the battery, sometimes dubbed "Range Anxiety". Turrentine *et al*. (Turrentine, Kurani 1995) interviewed drivers about the amount of additional range they would like, above expected trips. They call this additional capacity the "range buffer" and find that 20 miles is sufficient for most. More recently, an observational study of EV use patterns found that drivers would routinely use between 75 – 80% of available vehicle range, though only a single type of vehicle was used in the study, so that percentage could reasonably be translated into a fixed distance (Franke, Krems 2013). Thus, in design of EV range capacity, it seems reasonable to suggest that an automobile designer might add 20 miles to the driving range figures from the present analysis.

In general, this simplified analysis, assuming overnight, at home charging, shows that even with limited range, electric vehicles could provide a large fraction of transportation needs. When a driver has the ability to adjust or adapt travel plans on a few days per year, by substituting alternative transportation or charging during the day, even short-range electric vehicles can be satisfactory for a significant fraction of the population. Thus, understanding the customer's needs, and correctly segmenting vehicle buyers by range needs, appears to be a more cost-effective way to introduce electric vehicles than assuming that all buyers, and all drivers, need currently-expensive large batteries or liquid-fuel range extenders.

Chapter 6

INTRA-DAY CHARGING: INFRASTRUCTURE AND EV SUBSTITUTABILITY[18]

The analysis in the preceding chapter assumed that all vehicles would be parked at a 'home' location each night where they could be plugged in, and from which the driver would depart in the morning with a full battery. In this chapter, that assumption will be replaced with an analysis based on the locational parking patterns of the vehicles in the Commute Atlanta dataset described in sections 4.1 through 4.3. The results of the parking location analysis detailed in section 4.3 are used in this and in subsequent sections to inform charging location within the travel model. The charging location models corresponding to different levels of EVSE availability define when and where vehicles may be able to charge when parked between trips during the day, and when they may not be able to charge overnight because they are not at home. Much of this chapter and the next draw from the submitted paper Pearre *et al.* (Pearre et al. submitted).

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[18] This chapter and the next one draw from an under-review Pearre *et al* publication titled "Electric Vehicle Battery Size, Recharge Rate, and Charging Locations: Jointly Meeting Travel Requirements" (Pearre et al. submitted).

In section 6.1, an introduction and literature review reintroduces the topic of the ability of EVs to meet travel requirements, a concept that is described throughout this dissertation as 'EV substitutability'. In section 6.2 the metric of EV trip success is explained as it applies to this investigation of whether EV range can substitute for gasoline vehicle range, and results of trip success fraction for different charging infrastructure locations are presented and described. In section 6.3, these results are discussed in the context of vehicle and infrastructure design, and the basis for an economic analysis of vehicle and infrastructure optimization based on EV substitutability is laid out. In section 6.4, the results of model runs incorporating inter-trip, intra-day charging are presented in terms of Adaptation Days, the metric of substitutability introduced in section 5.4. In section 6.5 the basis of an economic optimization relating to the tradeoff between infrastructure development and vehicle capability is laid out. Finally, in section 6.6, the metrics of trip success and adaptation days are compared.

6.1 Introduction to Charging Infrastructure and EV Substitutability

The shift from liquid fuels to electricity entails a major shift in refueling infrastructure. Among other things, it is a radical shift in the concept of vehicle fueling. With today's expensive, flammable, and toxic liquid fuels, we have a centralized, commercial fueling infrastructure where vehicles stop primarily for the purpose of fueling, fill the vehicle in a few minutes and pay the supplier. With electric fueling, the recharge infrastructure will be widely distributed, mostly at locations where vehicles will be parked for reasons other than fueling (work, home), fueling is generally slow, required safety features are inexpensive and are built in to manufactured devices (charging station and vehicle), and the fuel is cheap and may not be paid for in a separate transaction, or may not even be separately metered (e.g. home charging).

As an example to establish the basis of this comparison, the US has approximately 280 million light vehicles, about one per adult. Today's liquid fueling infrastructure consists of about 120,000 gasoline stations (US Census Bureau 2011), or one fueling station per 2,300 vehicles. The cost of building a gasoline station (excluding property) is about $750,000[19], or $325 per vehicle served. The current installed cost of home recharging at moderate power (30 to 50 amperes) can be $1,000 to $3,000. If the average EV driver has two regularly used locations (e.g. home and work), thus two charging locations per vehicle, electric refueling could represent an order of magnitude increase in cost of fueling infrastructure, from the current $325 to $4,000 per vehicle. This simple calculation illustrates the order-of-magnitude differences in fueling infrastructure, presumably implying fueling behavior. Nevertheless, little

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[19] Gasoline station construction cost, not including real estate, range from $500,000 to $1M (data from Reed Construction Data, 30 Technology Parkway South, Suite 100Norcross, GA 30092), not including property cost. (For comparison, for a depreciated, operating station, sale prices range from $50,000 to over $1M on recent listings, e.g. http://gasstationsusa.com).

research has been done on charging rates and the relative importance of being able to charge at different locations.

One widely cited study on the subject of public charging infrastructure was conducted by the Tokyo Electric Power Company (TEPCO). TEPCO deployed a corporate fleet of Mitsubishi iMiEV electric vehicles, for each of which detailed driving records were kept to evaluate their serviceability (Anegawa 2009). During the course of the study, a fast charger (50 kW, DC) was installed within the test area, about 10km from TEPCO's central office. After the charger installation, average driving distance increased from 203 km/mo to 1427 km/mo. Another significant finding of the study was that with the 50 kW charger in place, EV drivers would return to the office with dramatically less charge remaining in the battery. Their conclusion was that public charging infrastructure is necessary to alleviate "range anxiety"; the fear of being stranded with a depleted battery. Other research into the psychological effects of driving an EV on travel behavior found much higher initial utilization of available range than the TEPCO study found (Franke, Krems 2013), suggesting that the seven-fold increase in driving range in the presence of a DC fast charger should not be considered typical.

Another field trial was conducted in the United States, when BMW placed 450 converted 'Mini' vehicles in the hands of private vehicle owners. Among their conclusions was that the limited range of the electric vehicle (70-100 miles per charge reported) did not encumber the mobility of the vehicle owner most of the time; 45% of study participants reported using the Mini-e for 90-100% of trips. Another significant result, somewhat contradicting the results of the TEPCO study, was that charging at home, overnight was adequate to satisfy the majority of the travel needs of vehicle drivers (Steinberg 2010). This is consistent with the results presented in Chapter 5, where it was found that more than 50% of the fleet could do 95% of their daily driving with 100 miles of driving range.

The range of results of previous research make the more detailed analysis of EV substitutability made possible with this travel model very important. In addition, the parking location analysis, with which the relative benefit and importance of potential charging locations can be evaluated, may be of great importance to policymakers in the discussion of transportation electrification, but has been largely ignored in previous research.

6.2 Trip Failures and Trip Success Fraction

The travel model at the core of this research operates by mapping the function of hypothetical electric vehicles, by way of their onboard energy storage (or 'state of charge'), onto the sample of observed gasoline vehicle trips. Through the year, the state of charge of the battery in each vehicle is tracked, rising when the vehicle is parked and charging, falling as the vehicle covers distance, and holding steady when it is parked at a location without charging infrastructure. A failure to match travel needs during a specific trip (or more simply a 'trip failure') is recorded whenever the state of charge of the battery drops to 0% (empty) during a trip. The relative frequency of trip failures is normalized for each car by the number of trips recorded in that car's monitoring period, and the resulting fractions are averaged across the fleet to provide a quantitative metric for each permutation of model inputs.

6.2.1 Charging at Home Only

The most basic and most likely scenario of charging infrastructure (at least for early adopters of EVs) is that in which cars have access to a dedicated EVSE when at home, but are only rarely able to charge at other locations. It is this scenario which the 'Daily Range' model described in Chapter 5 is intended to represent, though without recourse to parking location information. When parking location information is included, this scenario is described as the 'home only' charging scenario, for which the trip success fraction is plotted in Figure 11. The success fraction is simply (1 – failure fractions) in each modeled scenario.

To produce Figure 11, fractional trip success or failure rates were produced as described above, and mapped across different model inputs. In Figure 11, the range of battery capacities (translated into vehicle ranges via the conversion factor of 280 Wh per mile traveled discussed in section 2.4) is displayed on the X-axis, and part of the range of plug powers is displayed on the Y-axis. The surface generated is illustrated by a series of 'iso-success' lines, marked as the fraction of trips undertaken by the gasoline powered fleet that could be reproduced by a fleet of EVs of a given range and plug power, in percent.

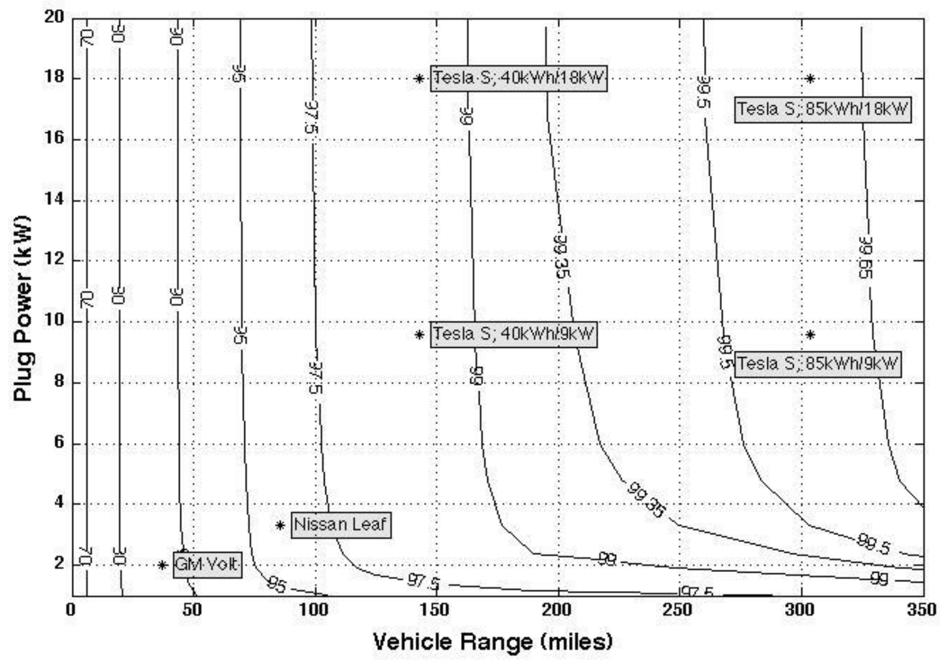

Figure 11: Round trip success fraction for charging at Home only.

Note that while plug powers up to 100 kW were evaluated, in Figure 11 only plug powers up to 20 kW are displayed, roughly corresponding to the limits of the U.S. Society of Automotive Engineers (SAE) standard J-1772, Level II, which limits charging to 240 Volts and 80 Amperes, or 19.2 kW. Above this level, plug size seems to have very little effect on failure rate (perhaps due in part perhaps to the exclusion of stops of less than ½ hour), so the plot was cropped for clarity.

To help interpret Figure 11 and put it into context, the approximate characteristics of several existing plug-in vehicles have been included, marked with asterisks (*) on the plot. As an example, a vehicle similar to a pre-2013 Nissan Leaf is placed on the graph at a location corresponding to its 24 kWh battery (calculated 85 mile range) and the car's internal 3.3 kW charger, fitted as a standard feature through the 2011 and 2012 model year (Gordon-Bloomfield 2012). At that location on the graph, it lies between the 95% and the 97.5% lines. This indicates that a car with those capabilities would successfully complete slightly more than 96% of the individual trips taken by the gasoline vehicles during the year, with only home charging. By contrast, a Tesla Model S with a top-of-the-line 85 kWh battery (and thus an inferred 303 mile range) and its standard 9 kW charger (Tesla 2013) could accommodate between 99.5 and 99.65% of all gasoline-vehicle trips. At the other end of both the battery range and charging power spectra, the Chevy Volt, a plug-in hybrid, accommodates about 88% of round trips with it's calculated 37 miles of electric range (Dennis 2010). (It should be noted that, being a hybrid, the 12% of trips that end in 'failure' in this analysis simply mean that the Volt's built-in gasoline engine is required to complete the trip.)

6.2.2 Charging at Home and at Work

When additional charging locations are included in the modeled scenario, more opportunities to top up the battery are presented, and thus fewer trips should end in a zero charge state (i.e., fewer trips are failed). The trip success fraction for the scenario where charging is available at Home and at Work is presented below in Figure 12. The same representative EVs are again depicted with asterisks (*) at the locations corresponding to their technical capabilities.

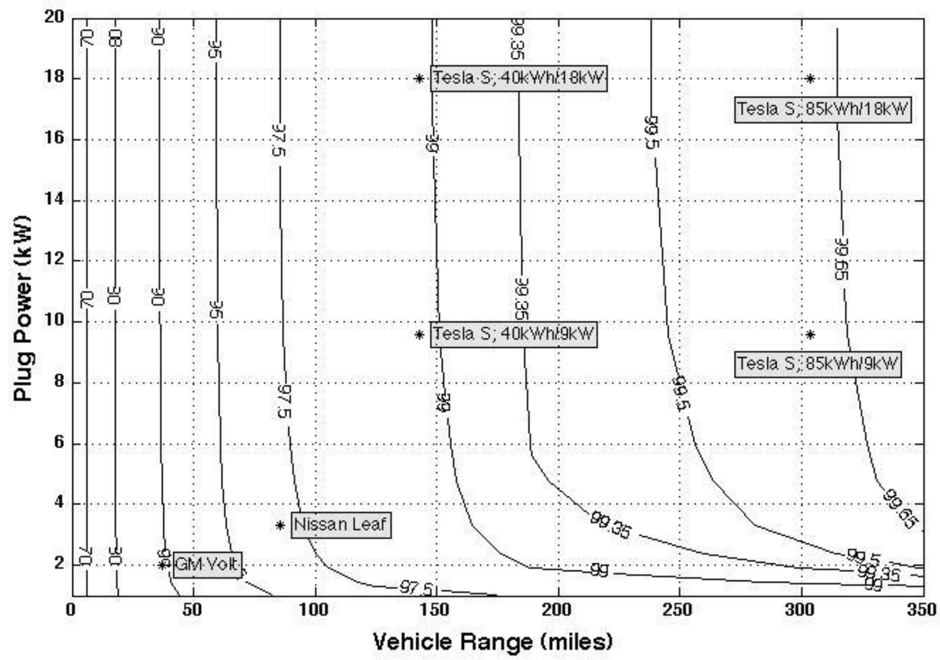

Figure 12: Round trip success fraction for charging at Home and at Work.

Comparing Figure 12 to Figure 11, the overall form of the success surface is very similar. Close observation shows that each 'iso-success' line has moved to the left and down, i.e., towards the origins along both axes. This relative position indicates that, as expected, an EV of any given capability will, with charging at Work in addition to Home, be able to successfully complete a somewhat larger fraction of its trips than charging at Home only.

6.2.3 Charging Everywhere

Extending the modeled charging infrastructure to the third scenario, in which EVSEs are available at every location at which vehicles park for more than 30 minutes, again produces a marginal improvement in trip success fraction. The results for the 'charge everywhere' scenario are presented in Figure 13. In Figure 13 the same six example vehicles are again demarcated with an asterisk at the location corresponding to their capabilities.

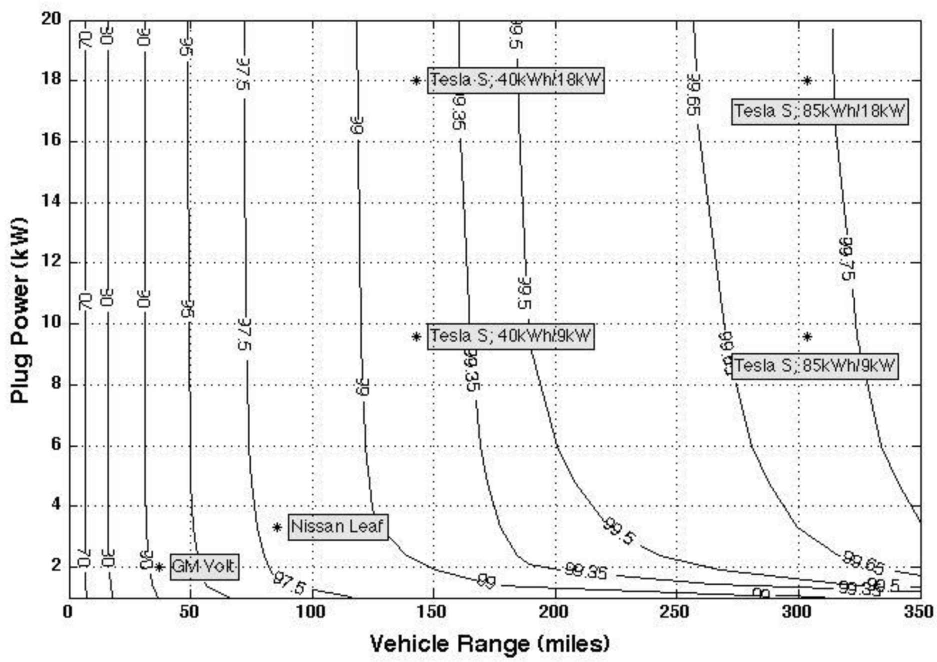

Figure 13: Round trip success fraction for charging at every parking spot.

In Figure 13 as in the two figures before it, the relative efficacy of higher power charging can be compared to that of improved range. This ratio can be seen in these three figures as the slope of the 'iso-success' lines: The steeper the (negative) slope, the greater the relative benefit of added range; the lower the (negative) slope, the greater the relative benefit of added charging power. The implications of these findings will be discussed in the next section.

6.3 Discussion of Trip Success Fraction Results

The three plots of trip success fraction presented in section 6.1 contain a lot of information. Some further consideration and interpretation of these results is necessary, and is presented below. This discussion is separated into a discussion of the effects of charging infrastructure, indicated by the differences between Figure 11, Figure 12, and Figure 13, and the effects of vehicle and infrastructure capacity, indicated by the differences seen within each of those figures.

6.3.1 Evaluating the Effects of Charging Infrastructure

Of particular interest in comparing Figure 12 and Figure 13 to Figure 11 is that the improvements in trip success are small, particularly in the areas of the graphs representing vehicles with more than 100 miles of driving range (the center and right-hand side of the plots). To facilitate the comparison, the success fraction values of the example vehicles have been tabulated in Table 2. In addition to the six vehicles demarcated in Figures 11 – 13, Table 2 also includes the hypothetical setup of long range EVs (with 40 and 85 kWh batteries, capable of covering 143 and 306 miles on a charge, respectively), with comparatively slow charge rates of 3.3 kW. The rate of 3.3 kW is of interest because it is the power available from a low-current 240V (in the US) or 230V (Europe) common residential outlets, drawing slightly less than 15 Amps. As such it represents an EVSE installation with only a minimal expenditure in residential wiring.

Table 2: Trip Success Fraction for example vehicles under different charging infrastructure scenarios.

Similar To	*Range*	*Charge Power*	Home Only	Home & Work	Everywhere
	(Miles)	*(kW)*	*(Success %)*	*(Success %)*	*(Success %)*
Tesla S	*143*	*3.3*	98.5	98.7	99.1
Tesla S	*143*	*9.6*	98.7	98.9	99.2
Tesla S	*143*	*18*	98.7	98.9	99.2
Tesla S	*306*	*3.3*	99.5	99.6	99.7
Tesla S	*306*	*9.6*	99.6	99.6	99.7
Tesla S	*306*	*18*	99.6	99.6	99.7
Nissan Leaf	*86*	*3.3*	96.6	97.2	98
Chevy Volt	*37*	*2*	87.7	89.5	91.6

In absolute terms, the advantage gained by less capable vehicles due to the emplacement of additional charging infrastructure is greater than that for the more capable vehicles. The Volt, for instance, completes almost an additional 2% of its trips on electricity when charging is added at work. The 40 kWh, 18 kW Tesla S by contrast only completes about 0.5% more of its trips when charging is added at work. The relative improvements will be examined in more detail in section 6.4.3.

6.3.2 Evaluating the Effects of Range and Charging Rate

The overall surface topography in Figure 11 though Figure 13 suggests some general principles relating to charging rate and range. If a car's goal is substitution for a majority of gasoline trips, a small battery is adequate and faster home charging does not make much difference. To demonstrate this, it is illustrative to follow lower and higher success rate lines for the 'home only' charging scenario in Figure 11. If a goal is 90% of trip success is set (significant gasoline displacement, but frequent reliance on alternative transportation), that goal can be met by a vehicle with only about 50 miles range and a 2 kW charge rate. Above 2kW (moving up the 90% line), higher charge rates have little apparent benefit, reducing the necessary range only by about 5 miles when a 20 kW charge rate is possible. On the other hand if the goal is higher, for instance meeting 99% of trips now served by gasoline, this can be met by distinct combinations. For example, the 99% line matches i) a 2 kW charger and about 240 miles range, ii) a 6 kW charger and 170 miles of range, or iii) a 19 kW charger and about 160 miles range. The tradeoff between solution i) and ii) is between a 6 kW and a 2 kW charger for a savings in installed cost of less than a thousand dollars, and 70 miles worth of additional batteries at about $8000.[20] In contrast, the tradeoff between solutions ii) and iii) is between a 19 kW and a 6 kW charger at a marginal cost (or

[20] Retail cost increase for a Tesla Model S, to upgrade from a 60kWh battery ($59,900) to an 85 kWh battery ($69,900), with other features identical, per Tesla' 's late 2012 offering for the Model S (Tesla 2013). This corresponds to a battery cost increment of $400/kWh, a little below DOE estimates, which we translate to $112 per mile of range.

avoided cost to the vehicle owner) of perhaps \$500-\$2,000[21], while adding an additional 10 miles of battery range, at an incremental retail cost of about \$1100.

Other general principles can be drawn from the form of the success surfaces. One of these is the non-linearity of required battery and charging to increase trip success. Going from 70% to 85% trip success (halving the failure rate) requires at worst about 25 miles of additional range. In contrast, a much smaller increment, from 99% to 99.5% (likewise halving the failure rate), requires over 100 miles added range. Very large increases in battery size and/or charging speed are needed to satisfy the last few trips per year, this in itself is a significant EV design consideration. This will be examined in more detail in section 7.1.

6.3.3 Comparative Analysis of Means of Success

As a guide for policy to steer the design and implementation of a new light vehicle transportation energy system, the three scenarios presented in section 6.1 can be used to compare the relative benefits of different design choices. Specifically, the relative efficacy of higher power charging and additional vehicle range can be compared to the effects of adding charging infrastructure at work or 'everywhere' in widespread public

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[21] These costs are estimated household wiring and marginal EVSE costs, based on general knowledge of electrical wiring, and do not include the costs of power electronics, which EPRI suggests would be at least \$300/kW power (Eckroad, Gyuk 2003), because power electronics of high capacity already exist in EVs.

locations. It must be noted that this analysis does not account for the impact on EV substitutability of charging available at just a few locations selected for EV promotion, which may in principle become trip destinations for EV drivers as gas stations are for conventional cars. Most existing public charging infrastructure seems to fall into this category, with EVSE emplacements at EV dealers, in front of city halls, and on 'Main Streets'; locations with high visibility, but little evidence of facilitating longer trips. Aspects of the design of public EV charging designed to enable longer trips are presented in Chapter 7, without specifying locations.

The application of this information is limited to very high level, probably governmental policy, because no one institution or company is in a position to make tradeoff decisions about all of these aspects of the transportation system. While a more detailed economic analysis of this tradeoff is both beyond the scope of this research and also likely to be very quickly made obsolete by the rapid development of the technologies and the markets, it is hoped that this analysis could assist in an economic optimization of key vehicle design parameters to optimize trip success fraction.

Table 2 illustrates the change in trip success fraction due to adding charging infrastructure at work and at all parking locations for each of 8 representative electric vehicles similar to those that are on the market. Using the home-only charging scenario as a base point, for each of those eight vehicles, the amount of additional vehicle range or charging power necessary to reach the trip success provided by the other charging infrastructure scenarios can be calculated from these data. The results of these calculations are presented in Table 3.

Table 3: Comparison of Methods to Increase Success Fraction for Home Only Charging

Similar To	*Range*	*Charge Power*	Range to Equal Home & Work	Range to Equal Everywhere	Power to Equal Home & Work	Power to Equal Everywhere
	(Miles)	*(kW)*	*(Added Miles)*	*(Added Miles)*	*(Added kW)*	*(Added kW)*
Tesla S	*143*	*3.3*	16.6	41.3	20.1	N/A
Tesla S	*143*	*9.6*	17.2	39.8	N/A	N/A
Tesla S	*143*	*18*	15.9	38.9	N/A	N/A
Tesla S	*306*	*3.3*	18.5	N/A	1.5	N/A
Tesla S	*306*	*9.6*	13.0	50.9	N/A	N/A
Tesla S	*306*	*18*	12.0	N/A	N/A	N/A
Nissan Leaf	*86*	*3.3*	13.2	33.9	N/A	N/A
Chevy Volt	*37*	*2*	7.3	15.4	N/A	N/A

In Table 3, several values are missing (listed as N/A). This happens when the range of analysis of the parameter in question (range or power) does not extend far enough to find a point of equivalency in trip success fraction. For example, for two of the three examples of cars that can travel 306 miles on a charge, no (assessed) amount of additional mileage would increase the success fraction as much as putting EVSEs at every parking spot. Given that the largest battery evaluated was 100 kW, corresponding to 357 miles of range, the maximum additional range assessed for those cars was 51 miles. It seems reasonable to infer that if greater single-charge ranges were evaluated, a solution would be found. Likewise, to achieve the success fraction in the home-only scenario equal to that of having plugs at home and at work by increasing the charging rate at home EVSEs only, solution are only found for the slowest-charging, yet high range vehicles. This finding corroborates the preceding observations that the relative marginal value of faster charging is greater for vehicles with greater range than for vehicles with shorter range.

More broadly, Table 3 suggests that for many vehicles, improvements in at-home charging power should not be considered as a means of increasing EV trip success. Bear in mind that the analysis extends to 100 kW charging, though the plots in Figures 11 – 13 were cropped at 20 kW. The cost of installing a second low-power charger at a frequent destination is likely to be far lower than getting fast-charging technology at home. It should be noted that there are reasons to adopt fast charging at home which will be assessed and discussed in Chapter 9, but trip success is not among them. In contrast to this finding, the amount of additional range required of an EV to match the success fraction provided by access to a second charger is fairly small, equivalent to 4 – 5 kWh of battery in all vehicle designs, while 30 – 50 miles of range (10 – 14 kWh) provides the same effect as having chargers everywhere.

While this finding may be counter-intuitive, it is the effect of averaging over the fleet. For individual vehicles that have a commute distance just over their full range, a charger at work will make an obvious difference. Thus, as a general policy, promoting chargers as work locations may be ill advised, but if assessed on a case-by-case basis, getting EVSEs in the specific work locations where they are needed should be of great value.

6.4 Adaptation Days

A single driving vacation or one long gasoline car trip spanning multiple stops for fuel or food, when applied to this EV substitutability analysis, is likely to be reflected as several trip failures. As a result, it may be more reasonable to return to the metric of substitutability used in Chapter 5; adaptation days. To do so, the analysis presented in sections 6.1 and 6.2 can be repeated using days, rather than trips, as the unit of analysis. In many cases, this may result in multiple trip failures aggregated into single day failures. Rather than normalizing the number of individual trip failures by the total number of trips each vehicle takes, in the following analysis vehicle substitutability is quantified by the number of days on which alternative travel arrangements would be necessary, and each vehicle is correspondingly normalized by the number of days on which it was in the study.

6.4.1 Adaptation Days for Home Only Charging

The 'adaptation days' metric is a reasonably intuitive measure of potential driver inconvenience, independent of the division of a day's travel into individual trips or trip chains. Renting a car for a family vacation, something that many people already to avoid wear and preserve residual value on their own car, serves as an intuitive example of how one adaptation on one day could take the place of several trip failures. The results presented Figure 11 in terms of trip success fraction for vehicles charging at home only are presented again in Figure 14 using the Adaptations Days measure.

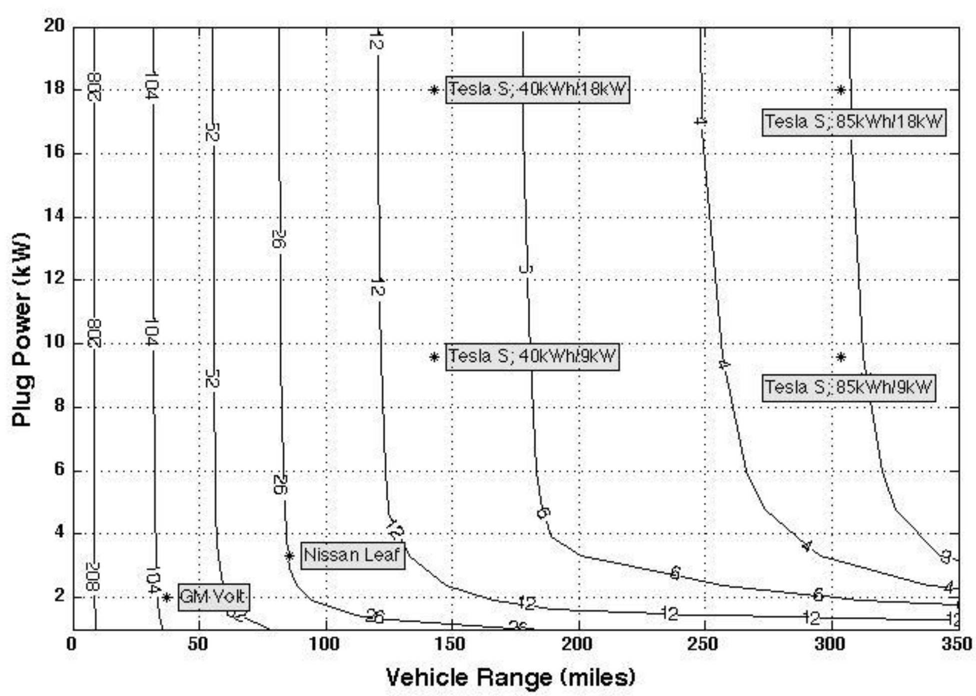

Figure 14: Average Adaptation Days for vehicles charging at Home only.

The isographic lines in Figure 14 (and in the next two figures) are lines of constant vehicle substitutability, or constant driver inconvenience, measured in adaptation days per year. As in the figures from section 6.1, the axes in Figure 14 are vehicle driving range (a function of battery size) and charging power. As before, sample points corresponding to the capabilities of several vehicles currently on the market are marked with asterisks. Figure 14 shows that an EV like the (pre 2013) Nissan Leaf, with a calculated 86 miles of range and a 3.3 kW charge rate, would require driver adaptation on average 26 times a year, or once every other week. A Chevy Volt with 37 miles of EV range should, on average, expect to need either the gasoline range extender, or some other adaptation, about 100 times a year (about twice a week), whereas a top end Tesla Model S would require adaptations only 3 days a year. All these figures are based on charging only at home.

6.4.2 Adaptation Days for Home & Work Charging

Adding charging equipment at work locations (as determined by the procedure described in Section 2.2), reduces the number and frequency of adaptations needed, as seen in Figure 15. Reduced need for adaptations can be seen by the lower numbers of adaptation days for the six example vehicles shown in the figures (these values will be tabulated in Table 4 in section 6.5), or by the leftward and downward movement of the isographic lines in Figure 15 relative to their positions in Figure 14.

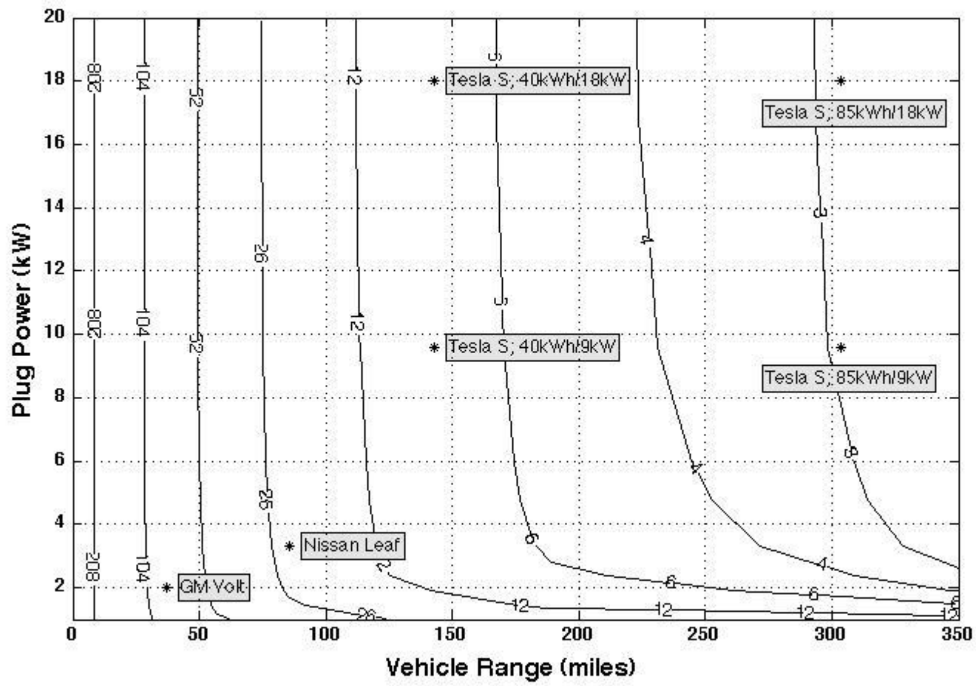

Figure 15: Adaptation Days for vehicles charging at home and at work.

As before, several vehicles are noted by asterisks on the plot in Figure 15 at locations corresponding to their capabilities. The comparison of Figure 15 to Figure 14 is thematically similar to that between Figure 12 and Figure 11, and as with the previous comparison, the differences are subtle. An evaluation of the differences, as they relate to the example cars will be made in section 6.4.

6.4.3 Adaptation Days for Charging Everywhere

In extending the charging infrastructure model to the third and final scenario, in which vehicles charge at any parking location, a further improvement in vehicle substitutability is anticipated. The results of this scenario are presented in Figure 16.

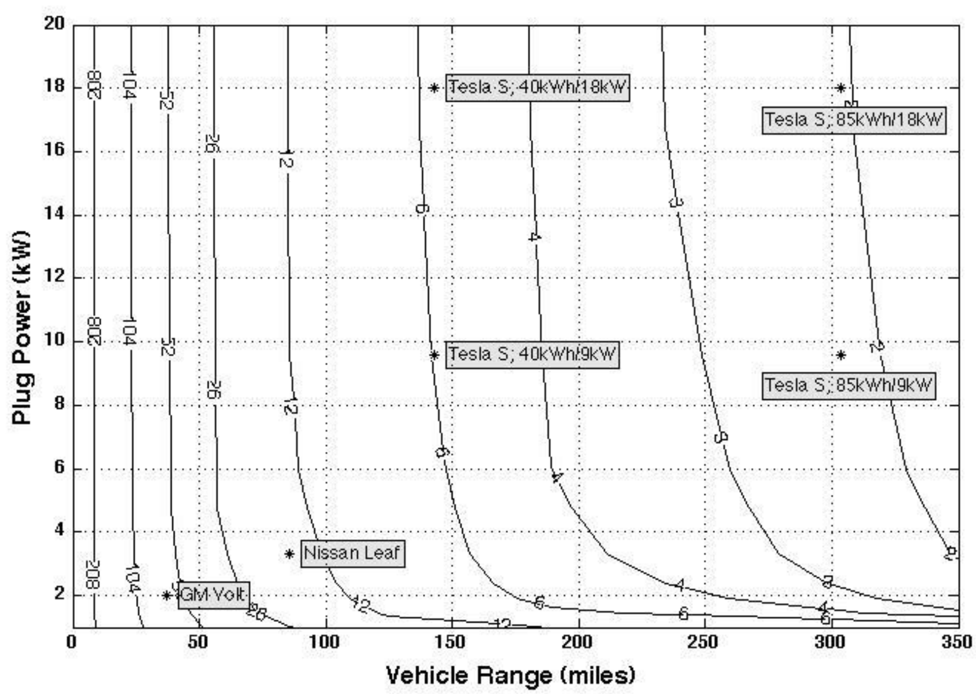

Figure 16: Adaptation Days for vehicles that charge at every parking location whenever they stop for more than ½ hour.

Figure 16 indicates that at all levels of vehicle capability, charging at all stops produces another modest improvement in EV substitutability by reducing the number of days on which an EV driver must adapt.

6.5 Discussion of Adaptation Days Results

Generally, the same conclusions can be drawn from these three analyses of adaptation days as were drawn from the analyses of trip success fraction as a function of charging infrastructure. These include the finding that for EVs with single charge ranges up to about 100 miles or so, the ability of increased charging power beyond about 6 kW to reduce adaptation days is almost non-existent, while for vehicles with greater driving range per charge, there is a more noticeable effect. A second observation consistent with the findings throughout the rest of this chapter is that the marginal capacity needed to avoid each successive adaptation day gets larger and larger. This effect is apparent in these three figures from the highly non-linear distribution, yet reasonably even spacing of isographic lines; those towards the left-hand side of each plot are separated by 100, 50, and 25 adaptation days, while those in the center and towards the right-hand side are separated by 1 day. As before, this is an effect of the long-tailed nature of the trip distance distribution.

6.5.1 Adaptation Day Effects of Charging Infrastructure

More specific results, relating to the effect of the three different charging infrastructure scenarios, are tabulated for the six example vehicles, and the two additional vehicles with higher range and low power charging, in Table 4.

Table 4: Adaptation Days for example vehicles under different charging infrastructure scenarios.

Similar To	*Range*	*Charge Power*	Home Only	Home & Work	Everywhere
	(Miles)	*(kW)*	*(Adap. Days)*	*(Adap. Days)*	*(Adap. Days)*
Tesla S	*143*	*3.3*	10.3	8.7	6.3
Tesla S	*143*	*9.6*	8.7	7.4	5.7
Tesla S	*143*	*18*	8.4	7.1	5.5
Tesla S	*306*	*3.3*	4.4	3.9	3.4
Tesla S	*306*	*9.6*	4	3.8	2.4
Tesla S	*306*	*18*	3.7	3.7	2
Nissan Leaf	*86*	*3.3*	25.3	20.9	14.1
Chevy Volt	*37*	*2*	93.3	77.4	60.2

Table 4 reveals a surprisingly linear, though probably coincidental, trend in the reduction of adaptation days between the three scenarios for vehicles with less than about 100 miles of range: Putting charging equipment at every parking spot reduces driver adaptation days about as much compared to just home and work charging as adding work charging does compared to just home charging. This result is telling, because the effort and expense of getting from the home-only charging scenario to the home and work scenario would be dwarfed by the cost associated with getting to the 'charge everywhere' scenario.

6.5.2 Comparing Infrastructure vs. Vehicle and EVSE Capability

A more interesting question that may be addressed from these results is the relative efficacy of infrastructure emplacement, charging power, and vehicle range to the goal of reducing adaptation days. This section thus parallels the analysis presented in section 6.3.3 and in Table 3. These data are presented in Table 5.

Table 5: Comparison of Methods to Decrease Adaptation Days for Home Only Charging

Similar To	*Range*	*Charge Power*	Range to Equal Home & Work	Range to Equal Everywhere	Power to Equal Home & Work	Power to Equal Everywhere
	(Miles)	*(kW)*	*(Added Miles)*	*(Added Miles)*	*(Added kW)*	*(Added kW)*
Tesla S	*143*	*3.3*	16.4	41.7	7.9	N/A
Tesla S	*143*	*9.6*	17.3	39.1	N/A	N/A
Tesla S	*143*	*18*	15.8	38.2	N/A	N/A
Tesla S	*306*	*3.3*	18.8	44.9	1.5	N/A
Tesla S	*306*	*9.6*	13.1	52.2	N/A	N/A
Tesla S	*306*	*18*	12.1	38.1	N/A	N/A
Nissan Leaf	*86*	*3.3*	13.9	35.4	N/A	N/A
Chevy Volt	*37*	*2*	8.0	16.7	N/A	N/A

As was the case with Table 3, Table 5 has many cells that exceed the range of analysis of the model, indicated by N/As. Though the metric being evaluated is very different, the results shown in Table 5 are strikingly similar to those presented in Table 3. This similarity indicates that the long-distance trip effect described in the introduction to section 6.3 is roughly consistent across the fleet; while it may still be the case that individual trip failures ‘clump’ during long road-trips into a small number of adaptation days, the effect of additional charging opportunities does not change the relative exposure of individual vehicles to such ‘clumps’ of failures.

6.5.3 Comparison of Success Metrics; Trips vs. Days

A more detailed comparison of the changes in trip success and adaptation days due to the various charging infrastructure scenarios can be found by comparing the proportional change in the two metrics between each pair of scenarios. These results are not likely to be of interest to policy makers or vehicle designers in themselves. Rather, subsequent researchers attempting related analyses may be aided by this evaluation of the similarities between the metrics. These results, tabulated in terms of fractional improvement (reduction of adaptation days and reduction in trip failure fraction) are presented in Table 6.

Table 6: Comparison of Success Fraction and Adaptation Days as Metrics

Similar To	*Range*	*Charge Power*	Trip Sucs. Change w. Work	Adap Days Change w. Work	Trip Sucs Change w. Everywhr	Adap Days Change w. Everywhr
	(Miles)	*(kW)*	*(% Improve)*	*(% Improve)*	*(% Improve)*	*(% Improve)*
Tesla S	*143*	*3.3*	15.9	15.2	39.6	38.6
Tesla S	*143*	*9.6*	16.3	15.5	39.2	36.8
Tesla S	*143*	*18*	16.1	15.3	39.5	37.1
Tesla S	*306*	*3.3*	10.4	10.4	31.6	31.3
Tesla S	*306*	*9.6*	7.7	7.5	30.2	29.7
Tesla S	*306*	*18*	7.0	6.7	32.6	32.8
Nissn Leaf	*86*	*3.3*	16.3	17.4	41.8	44.5
Chevy Volt	*37*	*2*	14.9	16.4	31.6	34.5

Table 6 suggests that the two metrics are substantially similar. Small differences do exist, associated with vehicle performance characteristics. In board terms, shorter range vehicles (the Nissan Leaf – like vehicle and the Chevy Volt – like vehicle) experience greater improvement in adaptation days than in trip success fraction due to increased charger availability at work and other locations. For longer range vehicles, the opposite is the case, with work charging added, trip failures diminish proportionally more than do adaptation days.

Each car of any configuration has a population of adaptation days. The average size of that population throughout the fleet is discussed in the preceding sections. Among that population of days (for each individual car), there is a distribution of the number of trip failures, i.e., on some adaptation days there was only one trip failure, on some there were two, on some three, etc. It seems plausible that for many cars, some specific days on which long trips were taken might include many trip failures per day, and that these few 'long distance days' might significantly influence the overall trip failure statistics. This theory presumes that these days are not workdays. If that were the case, then adaptation days that include stopping at work should include relatively few individual trip failures. Thus by adding at-work charging, the improvement in adaptation days should be greater than the improvement in trip failures.

Reviewing Table 6 this seems to only be the case for shorter-range vehicles. It seems plausible that the mechanism for this relates to distance covered to and from work, where 100 miles of range is likely to cover the vast majority of drivers. This explanation is supported by commute distance data from the National Household Travel Survey (USDOT-BTS 2003a, USDOT 2009). For longer range vehicles, however, the effect is weak or contraindicated. The weakness of this effect, however, is itself a result; because the changes in adaptation days and in trip failures are similar, it is reasonable to use either metric as a proxy for the other, where access to data is limited.

Chapter 7

DRIVER ADAPTATION

In the two preceding chapters, various tools and metrics were employed to assess the degree of inconvenience that limited-range EVs might pose to vehicle owners. In all cases, the analysis was concluded with some count or quantification of 'adaptations', be they actions needed to complete individual trips or to successfully replicate a full day's worth of travel. In this chapter, I examine in more detail what such adaptations might mean, specifically quantifying the implications for driver behavior for two particular adaptations that will likely be the most prevalent; en-route high-speed charging, and intra-household vehicle substitution. The content and form of this chapter are very similar to portions of the submitted paper Pearre *et al.* (Pearre et al. submitted).

In section 7.1 the unavoidable need for adaptation is reviewed through a thorough characterization of trip lengths relative to the three charging infrastructure models. In section 7.2, the charging time prior to long trips is evaluated and described, and the subject and inevitability of adaptation is briefly re-introduced. Section 7.3 quantifies of the degree to which onboard energy falls short of the task of completing the desired travel, examines the means by which this energy shortfall could be made up on the road through en-route charging, and compares that infrastructural and behavioral response to the existing liquid-fuel paradigm. Finally, section 7.4 examines the potential of limited range vehicles in multi-car households assuming that when available, some other car within the household will take any trips beyond the driving range of the EV.

7.1 How Long and How Frequent are Long Trips?

The answer to the question posed by the title of this section depends on the definition of a trip. The basis of the vehicle travel data used throughout this research is the notion that a "trip" is travel from one location where the vehicle is parked for at least ½ hour to the next. In evaluating the effects of electric vehicle serviceability to a human driver, it may be prudent to modify the unit of analysis to reflect the function of a limited range vehicle. Because charging is only available at specific stopping locations, it makes sense to define a 'trip chain' as a circuit of travel from one parking location with EVSE access to the next. A trip chain may thus be a single trip, or may be several trips and stops, terminating at the next charging station (or returning to the origin).

This modified definition does mean that EVSE availability affects the count of trip chains on any given day and in a year. More EVSEs mean more trips in total, but shorter trips, and a correspondingly lower proportion of longer trips. In the limit, with charging everywhere, the trip chain is equal to a "trip" as defined previously. Figure 17 illustrates the distribution of trip chain lengths found among the fleet for the three different scenarios of charging infrastructure. The bars indicate the relative frequency of trips of different lengths, in 5-mile increments. The lines show the exceedance probability; the fraction of trip chains that are longer than any given distance.

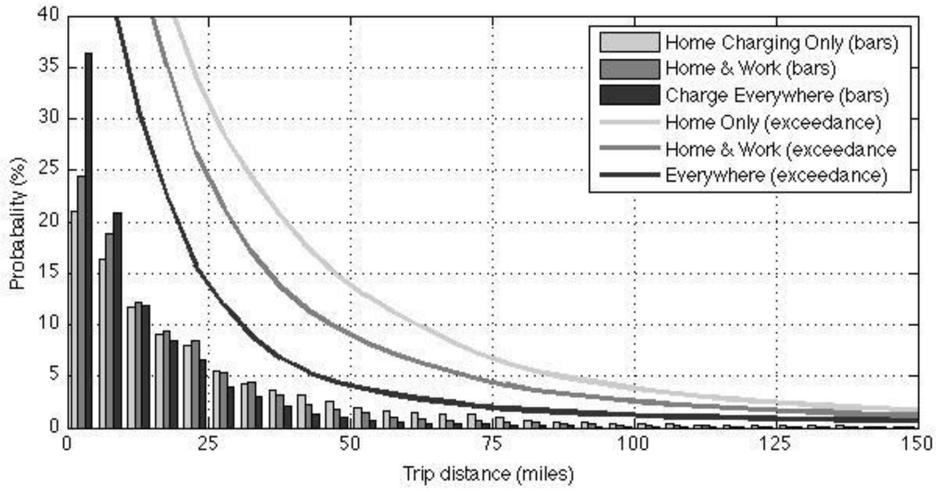

Figure 17: Distribution of distances of trip chains (EVSE to EVSE) for all cars throughout the year, applying three models of available charging locations.

As an example to aid in the interpretation of Figure 17, with home charging only, the exceedance line (light grey in Figure 17) indicates that roughly 14% of trip chains are longer than 50 miles. That means that on about one in seven occasions when a vehicle leave home, it travels more than 50 miles before returning home. In contrast, the middle line in Figure 17 shows that only about 9% of trips exceed 50 miles if charging is available at home and at work, while the darkest line in Figure 17 shows that if EVSEs are available at all stops, only 4% of individual trips exceed 50 miles (dark grey line).

Figure 17 makes clear that trip distance distributions have long tails, a fact also discussed in chapter 6. Figure 17 is a close analog to Figure 3 from Chapter 5, as both show the long-tail nature of travel distance distributions. The difference between them is that Figure 3 shows distances per day, while Figure 17 the distances driven in individual trips or 'trip chains'. Of particular interest in Figure 17 is the finding that even with charging at every stop, about 2% of trips exceed 150 miles of range (the maximum range plotted), while if charging is only available at home, about 4% of trips exceed 150 miles. Though beyond the limits of the plot, a vehicle designed to meet 100% of trips for 100% of cars would have to be able to drive over 1000 miles in a single trip.

Thus for practical purposes, EVs must be designed to meet the needs of slightly less than 100% of trips. If the driver can adapt from his gasoline vehicle behavior a few times per year, the vehicle's range requirements can be significantly reduced. Of course, most gasoline vehicles cannot drive 1000 miles without stopping either; they "adapt" by making refueling stops, which are not reflected in these data if they last less than ½ hour. A discussion of on-route refueling stops as they could apply to EVs is given in section 7.3.

7.2 Charging Time Preceding Long Trips

The preceding section established that long individual trips cannot be addressed by building more charging infrastructure. In this section, an analysis of the time spent parked preceding long trips will evaluate the extent to which fast charging can address long trips. If parking durations before long trips is consistently long, then charging faster could be a viable means of preparing for them. The distribution of duration of parking events at all locations, corresponding to the 'charge everywhere' scenario, preceding long trips (over 150 miles) is presented in Figure 18.

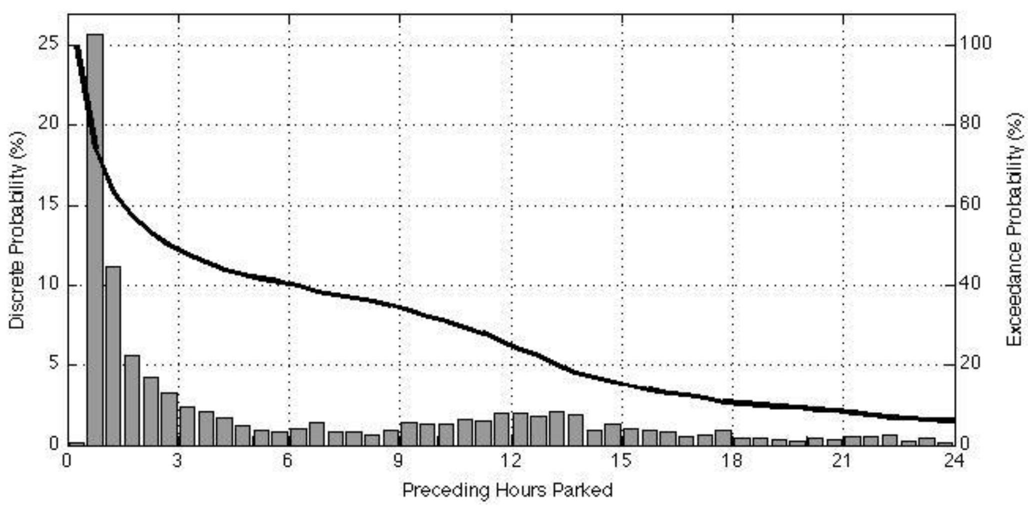

Figure 18: Time parked preceding trips over 150 miles.

In Figure 18 discrete probabilities of each 30-minute duration bin are displayed as grey bars with a frequency scale on the left vertical axis. For example, the second bar gives the relative frequency of parking durations lasting between ½ and 1 hour, which occurs just over 25% of the time. This means that prior to 25% of long trips, the vehicle is parked for less than an hour. (Note that within this data, stops of less than 30 minutes were ignored, as evidenced by the extremely low frequency of stops less than half an hour). The exceedance probability of any pre-trip parking duration is given as a continuous black line, with a scale on the right vertical axis. This figure shows that fully half of trips over 150 miles are undertaken after less than 3 hours parking.

I had expected that a significant fraction of long trips would start immediately after overnight parking. There is indeed a bulge around 9 to 15 hours of parked time prior to a long trip—but that range, together, accounts for only about 20% of the long trips. It is apparent that many 150-mile trips are taken after a stop for a meal, after work (where parking durations would be less than 9 hours), from a work location to another site, or after running errands to prepare for the trip. The short charging followed by long trip is an important scenario to understand better in order to develop EVs that meet more of our driving needs. Either a larger battery or faster charging will improve an EV's ability to make long trips after these short charge times. Of course, planning ahead on the part of the driver may be effective (and free) for some of these combinations of short park and long trip.

From this analysis in conjunction with that in section 7.1, it must be concluded that limited range and slow charging electric vehicles cannot be substituted for gasoline vehicles without some occasional compromise or adaptation of travel patterns. Luckily, those adaptations need not necessarily be exceptionally burdensome or arduous. Methods of adaptation that drivers could use to avoid getting stranded were discussed in chapter 5 and the paper from which it was drawn (Pearre et al. 2011), and might consist of:

> 1) substituting a liquid fuel vehicle (use another car in the household or rent a gasoline car), 2) recharging during the day or en route, 3) delaying part of the travel until the next day (e.g. instead of 3 side errands after work, two are done one day and the third the next day), or 4) choosing a different mode of transport (commuter rail, bus, air, etc) (Pearre et al. 2011).

Of the adaptations proposed and quantified but not evaluated for driver impacts in Chapter 5, this chapter explicitly models and quantifies adaptation 1), vehicle substitution in multi-car households, and adaptation 2), differing availability of charging stations en-route.

7.3 Energy Shortfall and the 'Gas Station' Model

As discussed in the literature review, there may be a psychological effect associated with the knowledge that fast-charging infrastructure exists 'on the road', but more concretely, the use of such infrastructure would permit EV drivers to recharge their vehicles en-route and complete trips they otherwise could not. Such an infrastructure model is similar to the existing state of gasoline refueling; when the remaining onboard energy (gasoline) gets low, vehicles are taken to specific locations where more energy can be taken on quickly. Thus for this discussion a distinction must be made between the previous 'base' charging locations (Home, Work, etc.), and these new hypothesized 'en-route' stations.

With this travel model it is possible to calculate the degree to which each vehicle configuration would rely on such en-route charging, assuming they are available where and when needed, as gas stations are today. For each vehicle, the additional amount of energy needed to complete each 'failed' trip through the year was calculated. These values, the 'Energy Shortfalls' for each trip, were summed through all trips during the year and normalized by the amount of time each vehicle spent in the study. The result is a total energy shortfall for each vehicle, measured in kWh, which were then averaged across the fleet. Dividing energy shortfall by possible fast-charger powers produces a duration, in hours per year, that vehicles would need to spend at en-route charging stations. To simplify the results only 'Home' charging at the popular and practical level of 6.6 kW and roughly the J-1772 Level II maximum value of 17 kW were assessed at various 'en-route' charging powers. Thus Figure 19 shows the necessary time, in hours, that vehicles with 6.6 and 17 kW at home charging would need to complete all trips.

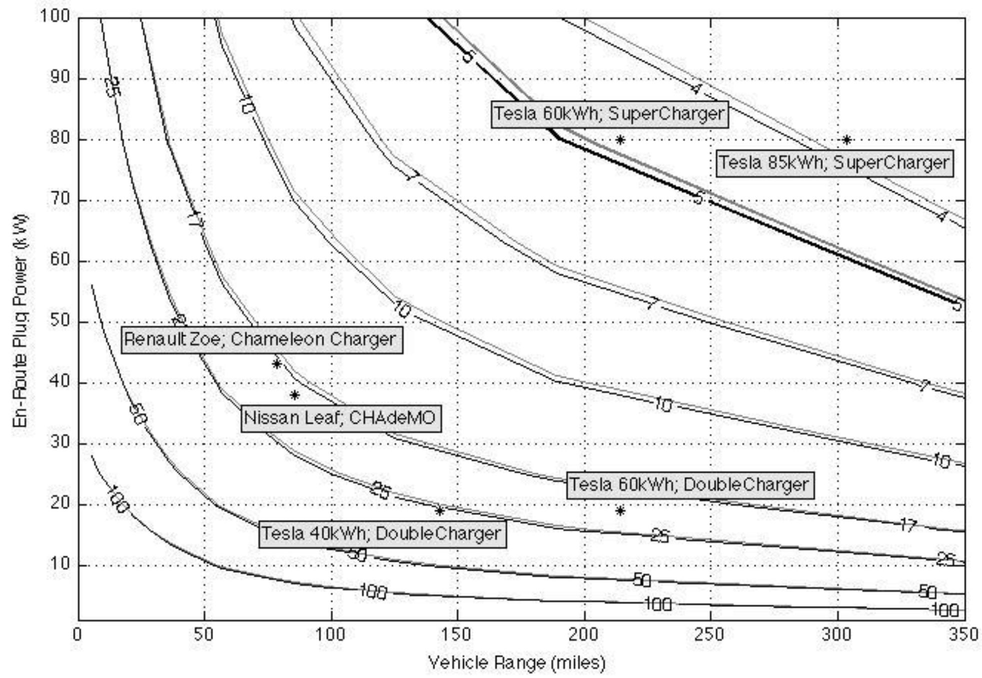

Figure 19: Additional time (hours) at en-route fast charging stations to complete all trips. Vehicles are assumed to have 17 kW (black lines) or 6 kW (grey lines) EVSEs at home only. Liquid fueled vehicles spend about 5 hours per year (highlighted) refueling.

Figure 19 also includes the names and positions of several ‘rapid’ or high-power charging technologies. These will be discussed in greater detail in chapter 11, but for the purposes of this analysis are intended to indicate the potential tradeoff of vehicle and infrastructure capabilities. It should be noted that many vehicles will limit charge rate to preserve battery life, so initial charging power values may not represent the entire charging cycle. These results, however, are not dependent on filling the battery to 100% state of charge at any fast-charging en-route stop, but just tabulate the total amount of time needed at such stations to complete all trips.

Figure 19 suggests that a vehicle with greater than 6 kW at-home charging and 250 miles range would spend about 5 hours at 70 kW en-route charging stations if such charging was available wherever it was needed. This can be compared with average gasoline vehicle statistics. A vehicle that drives 12,000 miles in a year that gets 27 mpg consumes 444 gallons of gasoline in the year. Drivers refill about 2/3 of a tank, or about 8 gallons at each fill-up (Turrentine, Kurani 1995, NACS 2012), so about 50 fuel stops are needed in a year. This agrees reasonably well with self-reported survey data indicating 55 fuel stations visits per year (GasBuddy.com). Each of these consists of, on average, 5.6 minutes stopped at the gas station, so on average, drivers spend 4.6 hours per year at gas stations (Adornato et al. 2009), plus some amount of time in transit to the station from the driver's route (only 7% of refueling is not part of some other travel (Kitamura, Sperling 1987)). Total travel time to reach a refueling station from a home or work location has been estimated as 3 – 7.5 minutes (Kitamura, Sperling 1987, Melaina 2003, Nicholas 2004), but the amount added to an existing trip is likely to be far lower. If the marginal travel is 2 minutes, then in 50 refueling events a total of 1.7 hours per year will be dedicated to getting to gas stations.

In contrast, if home recharging predominates as the analysis in chapter 6 suggests, then additional time to charge an EV should similarly be evaluated. Noted EV proponent and reporter Robert Llewellyn estimated that plugging in an EV would add

9 seconds to the act of parking at home[22], and the personal experiences of the researchers at the Center for Carbon-free Power Integration research group, including myself, agree. If the same 9 seconds are attributed to unplugging the car before use, and 365 such events occur in a year, then about 1.8 hours would be dedicated to home charging. The uncertainties around this number and the marginal travel time to a gas station are large, so they may be considered equivalent. Correspondingly, the line corresponding to 5 hours of en-route refueling per year has been highlighted on Figure 19 to facilitate comparison.

While high capacity plug-in vehicles could, according to this analysis, spend the same amount of total time at en-route recharging stations as liquid fueled vehicles, the distribution of such events would be different. Whereas liquid-fueled vehicles have some discretion as to when and where to refuel (Kitamura, Sperling 1987), and 5 minute stops would be distributed somewhat evenly throughout the year, for even a 250 mile EV with a 17 kW EVSE at home, those 5 hours would be clumped into a few long events during the 4 or so adaptation days when home charging is insufficient (Figure 14).

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22 Access online Feb 4, 2013: http://www.youtube.com/watch?v=DQkGw-U9-ps&list=UUnpzRVNV6o8Lekp2K8V8njQ&feature=player_detailpage

7.4 Multi-Vehicle Households

In using the driving patterns of internal combustion vehicles throughout this research, a "worst case" for the substitutability of electric vehicles is evaluated, in that no changes in driver behavior are reflected in the results. In the United States however, roughly 60% of households own more than one vehicle (USDOT-BTS 2003b). For such households, when a long trip or a driving-intensive day is anticipated, if at least one of the household's vehicles is compatible with existing liquid refueling infrastructure it would in principle often be simple to take the fueled vehicle rather than the EV. The roughly 60 million households in the U.S. to which this condition could apply far exceed any policy or sales goals for EVs within the next several decades. The breakdown of household vehicle ownership in this sample is given in Table 7, which shows ownership rates similar to national averages (USDOT-BTS 2003b); 167 households in the study own more than one car.

Table 7: Population of Households with singe vs. multiple vehicle ownership in Study Sample and in U.S. National Average

	Single Car	Two Cars	Three or More
NHTS Nat'l Ave	34.2%	40.5%	25.2%
This Sample	37.9%	45.2%	16.9%

The concept of households with at least one liquid fueled vehicle and at least one limited range EV was described by Kurani *et al.* (Kurani, Turrentine & Sperling 1996) as a “hybrid household”, and was included as one of the possible mechanisms of travel adaptation in Chapter 5. Some previous research on the effects of hybrid households employs methodology very similar to that used in this research. Kahn & Kockelman examine 255 households for a year and suggest that 100 miles of EV range should substitute for 80% of multi-vehicle households with 4 days per year of travel adaptation (Khan, Kockelman 2012).

The analysis of this subsample of the population with more than one vehicle per household was undertaken as part of this study. To keep the results realistic and conservative, the assumption was made that vehicle exchanges would only happen at home. This form of adaptation will be referred to as intra-household vehicle substitution. For each of the 167 multi-vehicle households, a list of trips the household’s EV would likely take was constructed by i) finding times when all household vehicles were in use simultaneously (*T1*), ii) identifying the next swap opportunity (when at least two vehicles were at home, *T2*), iii) finding the preceding swap opportunity for those vehicles (*T0*), and iv) assigning to the EV the home-home round trips undertaken between *T0* and *T2* by the vehicle that had the lowest cumulative round trip mileage in that period.

In simpler terms, the multi-vehicle household model simulates drivers selecting a gasoline vehicle for long trips when one was available. The resulting set of trips was evaluated for adaptation days as before, contingent on vehicle capabilities. The results, which may be compared directly to those presented in Figure 14 for individual vehicles, are presented in Figure 20 for multi-vehicle households.

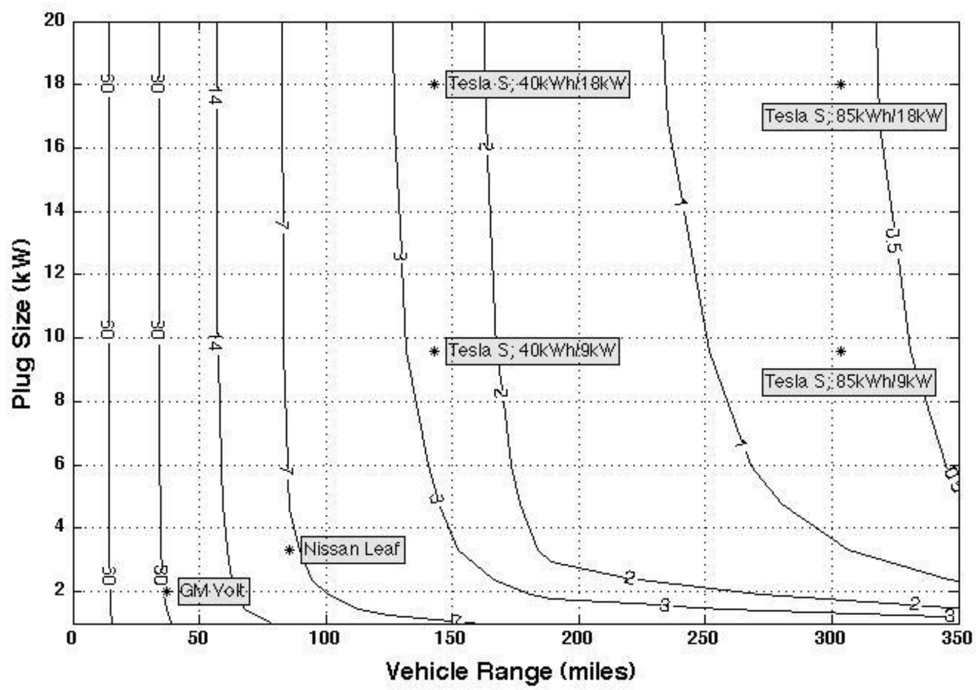

Figure 20: Adaptation Days per year for hybrid households, where the EV driver uses a liquid-fuel vehicle for long trips, if available. Home charging only.

While intra-household vehicle substitution significantly improves trip success rates, the number of adaptation days does not drop to zero. The reason for this may be the presence of some outlying households for which travel for all vehicles frequently exceeded the capacity of even the longest-range plug-in vehicles analyzed, or poor parking location characterization; because the results presented are the average of the fleet, any single vehicle for which a Home location was poorly characterized would prevent a zero average.

An alternative presentation of these findings that may be more tolerant of statistical outliers or poorly characterized parking locations is to calculate the fraction of these multi-vehicle households that never have to adapt their travel (in one year). The results of this analysis, again for charging only at Home, are presented in Figure 21, where the isographic lines represent the percentage of multi-car households that never have to adapt travel.

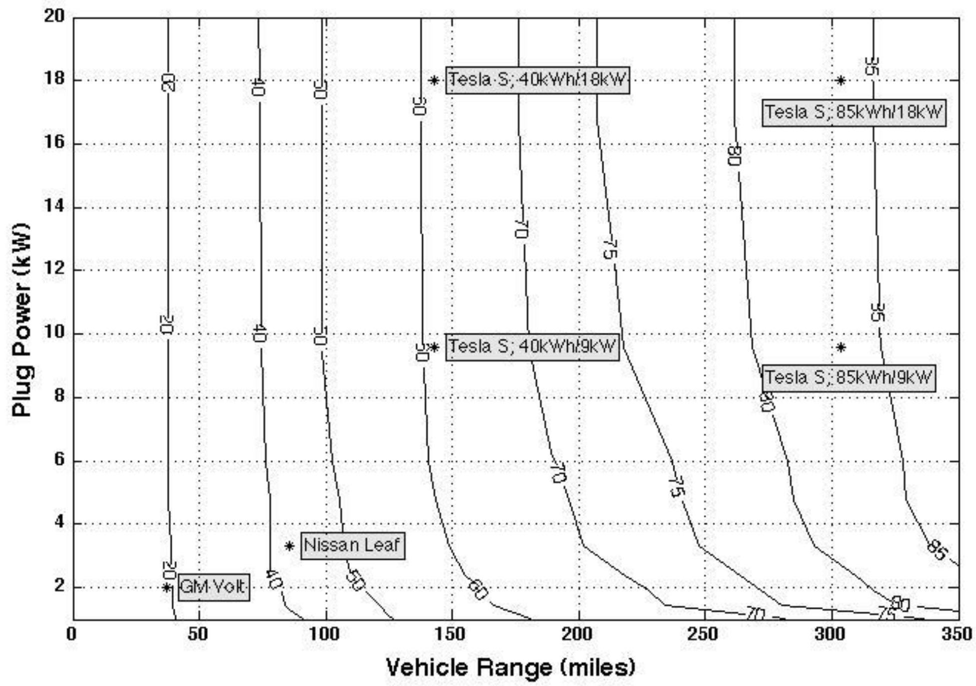

Figure 21: Fraction (%) of Multi-Vehicle Households that never require travel adaptation if one vehicle per household is an EV. Home charging only.

In Figure 21 it can be seen that, for instance, the top end Tesla Model S, with 18 kW charging and an 85 kWh battery would fit into about 84% of multi-vehicle households without requiring a single travel adaptation all year, other than switching cars within the household (which the prior analysis did count as an adaptation). Similarly, about 43% of multi-vehicle households could substitute an EV with characteristics of a Nissan Leaf for one of the household's vehicles and never have to adapt their travel patterns.

The preceding analysis has provided quantitative analyses of the influence of charging infrastructure and multi-vehicle households on the degree to which plug-in vehicles can substitute for conventional vehicles in the U.S. private fleet. The primary results from chapter 6, EV substitutability measured in adaptation days, are presented in Table 8 with the results of this multi-vehicle household analysis appended. The same eight example vehicle configurations used throughout the analysis are assessed.

Table 8: Adaptation Day Count compared among different modeled scenarios, for various plug-in vehicle configurations.

Similar To	*Range*	*Charge Power*	Home Only	Home & Work	Everywhere	Multi-Car House
	(Miles)	*(kW)*	*(Adap. Days)*	*(Adap. Days)*	*(Adap. Days)*	*(Adap. Days)*
Tesla S	*143*	*3.3*	10.3	8.7	6.3	3.1
Tesla S	*143*	*9.6*	8.7	7.4	5.7	2.5
Tesla S	*143*	*18*	8.4	7.1	5.5	2.4
Tesla S	*306*	*3.3*	4.4	3.9	3.4	1.3
Tesla S	*306*	*9.6*	4	3.8	2.4	0.9
Tesla S	*306*	*18*	3.7	3.7	2	0.6
Nissan Leaf	*86*	*3.3*	25.3	20.9	14.1	7.4
Chevy Volt	*37*	*2*	93.3	77.4	60.2	28.8

Table 8 shows quantitatively that regardless of the size of battery and speed of charge, having access to more charging locations reduces the number of adaptation days, however, these gains are very small compared to the effect of intra-household vehicle substitution. In Table 9, the same model conditions and example vehicle configurations are compared by the metric of the fraction of households that require no adaptation. Note that while Figure 21 referred to the fraction of the population of multi-vehicle households, the results presented in the "Multi-Car Household" column of Table 9 have been normalized by the entire population of the study. Thus a vehicle with 143 miles of driving range and 3.3 kW charging could be the EV in 36.5% of *all* households, with no adaptation days, if intra-household vehicle substitution is not counted as an adaptation.

Table 9: Fraction of all households that never require adaption when multi-vehicle households operate as 'hybrid households', for selected example vehicles and charging availability.

Similar To	*Range*	*Charge Power*	Home Only	Home & Work	Everywhere	Intra-House Substitution
	(Miles)	*(kW)*	(Houses %)	(Houses %)	(Houses %)	(Houses %)
Tesla S	*143*	*3.3*	11.2	11.9	22	36.5
Tesla S	*143*	*9.6*	11.4	12.6	25.3	37.9
Tesla S	*143*	*18*	11.7	12.8	25.5	38.2
Tesla S	*306*	*3.3*	31.1	32	48.2	50.4
Tesla S	*306*	*9.6*	32.8	33.4	52.8	51.9
Tesla S	*306*	*18*	33.5	34.2	53.9	52.1
Nissan Leaf	*86*	*3.3*	4.8	4.8	8.1	27.2
Chevy Volt	*37*	*2*	0.4	0.4	1.3	11.8

Table 8 and 9 show that, at least for the majority of U.S. households, the effect of intra-household vehicle substitution –a form of adaptation- is dramatically greater than even ubiquitous chargers. For the 60% of US households have more than one vehicle, this adaptation can be accomplished with no equipment cost, and for many, little inconvenience. Thus it would seem that such households are a logical target of EV marketing, much more than they have been to date. Due to the enormous potential size of this market (one vehicle in each of about 60 million households), by the time this market is anywhere close to saturated with one EV each, batteries might very reasonably be expected to be much higher capacity and lower cost.

Chapter 8

EV-SOURCED GRID LOAD DUE TO CHARGING

Much of the research related to electric vehicles focuses on the potential interactions between the vehicles themselves and the electrical grid. Within that field, the principal focus has been on the potential damaging effects of additional load. For high penetrations of EVs and ubiquitous charging infrastructure, it will be important for vehicle charging to become more intelligent that today's 'dumb' battery devices, which begin charging when first plugged in and charge as fast as the battery management system will allow until the battery is full. The effects of such 'dumb' charging, though likely of little significance to the electricity transmission system Shao, Pipattanasomporn & Rahman 2009, Pearre et al. 2011), have been demonstrated to at least potentially be significant to the distribution system at even very low plug-in vehicle market penetrations (Lemoine, Kammen & Farrell 2008).

In this chapter, I will quantify the observed grid loading revealed by the EV travel model described in the preceding chapters, and explore how it changes as a function of the several vehicle and infrastructural parameters discussed throughout this research. The concept of 'charging algorithms', reviewed in the literature in section 2.3, will be reintroduced and included as a model variable in the last two sections of this chapter. Section 8.1 will present a brief reintroduction of the topic. In section 8.2, grid load through time will be examined as a function of the three charging infrastructure models described in the previous chapters. Section 8.3 will present a more succinct characterization of impacts and compare a variety of scenarios. In 8.4, the charging algorithms examined in the model will be reintroduced, and their effects on EV substitutability discussed. Finally, section 8.5 will examine the effects of charging algorithm on grid load in greater detail.

8.1 Grid Load due to Charging

One of the most fundamental areas of concern that can be addressed from this analysis is the amount of electrical load the fleet of plug-in cars impose on the grid, and at what times of day at which that load is imposed. The answer to this question varies with each of the variables used to define the travel model. As a simple example, if the entire fleet is assumed to consist of plug-in vehicles with i) 16 kWh of battery capacity, ii) that are able to charge at a rate of 3.4 kW, iii) will charge only at home, and iv) will charge immediately upon parking, then the load imposed by the aggregated fleet is described by the curves in Figure 22. The plot on the left in Figure 22 describes the load seen on workdays, while the plot on the right describes the load seen on weekend days and holidays.

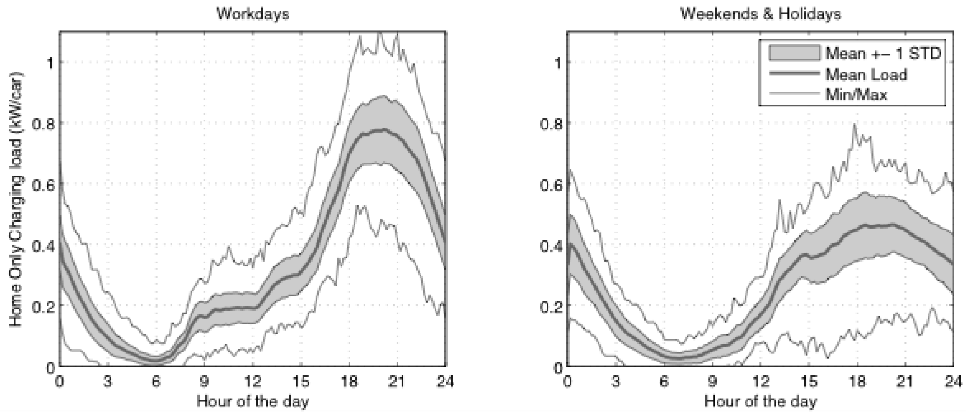

Figure 22: Grid loading due to travel electrification based on a moderate-size vehicle with 16 kWh battery and 3.4 kW charging power (240V @ 15A)

In Figure 22, for the left plot a total of 251 workdays were included, and there are 110 weekend and holiday days incorporated into the right plot. Each of the individual day load curves was normalized by the number of cars in the study on that day, so the results seen in Figure 22 (along with those in subsequent figures in this chapter) are in kW of power draw per car. Two days at the start and end of the dataset were discarded due to uncertainty as to the number of participating vehicles, resulting in 251 and 110 load curves represented in the left and right plots of Figure 22 respectively. The mean of these curves, at each 10-minute time increment throughout the day, is shown as a thick black line, and one standard deviation about that mean is shown as the grey band. The minimum and maximum load at each 10-minute point is included as a thin black line.[23] . In subsequent figures, only the average load line will be presented.

As can be seen from Figure 22, peak evening load occurs on week days in the evening hours after people return home from work and plug in, and those peaks average about 800 W of load (0.8 kW) per EV. At other times, loads are smaller, and drop to near zero in the early morning through the middle of the day. By comparing the load-through-time plot here with the plot of fleet fraction at home plot (Figure 2), it can be inferred that the low load in early morning is because most vehicles, though plugged in at home, have finished recharging.

Fig 1 is based on a simple model of charging. The temporal distribution of load may be expected to change as vehicle capabilities and characteristics change, and the assumed charging infrastructure changes. How these changes affect the load curves is the focus of the following sections.

8.2 Effect of Vehicle Design and Infrastructure

In Chapter 6, the effects of charging infrastructure, i.e., where vehicles are able to charge between trips, on EV substitutability were examined in detail. Here, the same

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[23] Note that maximum and minimum loads at any time (6:10pm, for instance) do not necessarily occur on the same day of the year as maximum loads in adjacent times (6:00 or 6:20pm in this example).

three models of charging infrastructure buildout; ‘home only’, ‘home and work’, and ‘everywhere’, are assessed for how they influence the load curve. Because many configurations of vehicle battery size and charging power may be of interest, many different configurations have been included. Where in Figure 22 the grid loads due to a single vehicle configuration were plotted and characterized by a mean, standard deviation, and extreme values, varying through time, in Figure 23 the daily load of many different configurations of vehicles are shown as a function of the hour of the day. As before, in this section I assume no active control of charging—the timing and rate of charging are influenced only by the amount of prior driving, the battery size, and the charging rate. Also, plots on the left are average hourly loads on workdays, while plots on the right are average hourly loads on weekends and holidays. The three rows of load plots correspond to the three charging infrastructure models; i) charging at home only, ii) charging at home and at work, and iii) charging anywhere.

Each of the six plots in Figure 23 shows grid load for high and low power charging for the full range of vehicle battery sizes discussed. Thus, each plot has seven grey curves showing the grid load imposed by vehicles with 1.5, 3, 6, 10, 24, 53 and 100 kWh batteries charging at 17 kW chargers, and seven black curves for the grid load imposed by vehicles with the same set of battery sizes charging at 2 kW.

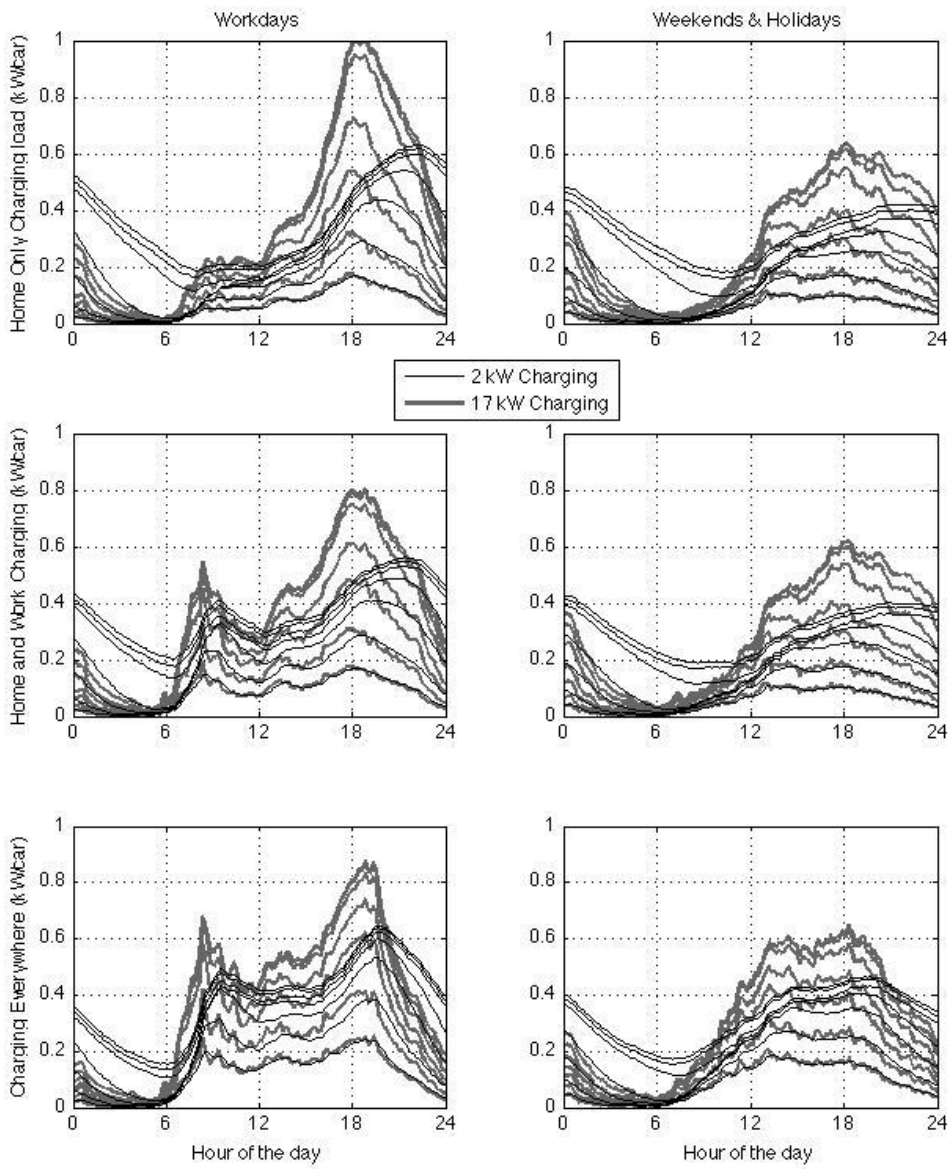

Figure 23: Grid loading through weekdays (left) and weekend days (right) of Plug-in vehicles with 1.5, 3, 6, 10, 24, 53 and 100 kWh batteries charging at 2 kW (thin black line) and 17 kW (thick grey line) at home only (top), home and work (middle), and any parking location (bottom).

In the uppermost two plots of Figure 23 the effects of increasing battery size for vehicles charging only at home are potted. As battery size increases, the load on the grid at any point in time increases. At higher power charging of 17 kW (grey lines) on workdays (left plot) the time of peak load remains in the vicinity of 18:00 regardless of battery size, which presumably corresponds in large part to drivers returning home after work. The height of the peak however, indicating the magnitude of the load, increases with battery capacity, though in a highly non-linear fashion. As discussed in Chapter 6, marginal battery capacity has a decreasing incremental effect on travel success, as the frequency with which drivers cover any given mile (or need any given kWh) decrease with additional miles or range. Here it is evident that marginal battery capacity has a correspondingly decreasing marginal effect on grid load. While each successive battery is about twice the capacity of the previous, between a 10 kWh battery pack up to the largest pack evaluated (100 kWh), peak loads increase from about 750 W to about 1000 W per car, with the highest three curves, representing 24, 52, and 100 kWh batteries showing almost no differentiation. This similarity of loads for larger batteries, reaching a maximum at about 1 kW per car, is evident even though each of these cars is capable of charging at 17 kW.

With lower power charging (2 kW) at home only on workdays (black lines in the top left plot of Figure 23) a similarly small effect of increased battery size is seen by the bunching of the lines towards the top of their distribution. Of note though, is that 2 kW charging, when compared to 17 kW charging, both reduces and delays the load peak. Increasing battery size for low power charging likewise seems to delay the load peak.

Both of these effects can be explained as the accumulation of concurrently charging vehicles; when vehicles with large batteries charge from low-power plugs, many of the vehicles that started charging at 5pm will still be charging 4 hours later at 9pm, so charging load will accumulate throughout the period of the evening when vehicles are returning home. With high power charging, batteries fill quickly, so the load profile more closely matches the rate at which vehicles arrive at charging locations. In both cases, load will only taper as batteries fill, and the rate of batteries filling will at some point match and then exceed the rate of new vehicles arriving home. When charging power is high and batteries fill quickly, this point occurs early in the evening, but when charging power is low, it does not occur until 9pm or later for batteries of 24 kWh or more capacity. On weekends a much lower and broader peak suggests much less coincidence of travel and return home.

When charging at work (middle plots) is added, the most striking difference is the reduction in loading for large batteries on high-power chargers, presumably due to the reduced charging needs of vehicles that only had one direction's commute worth of energy to replenish. A morning load peak, corresponding to the arrival of vehicles at work, is evident between about 7:00 and 10:00. This morning load peak once again shows the peak delaying effect of lower power charging. As before low power and large batteries make for a smoother load curve, but may be presumed to correspond to frequent trip starts with a battery not yet full. The load profiles experienced on weekends and holidays are almost entirely unaffected by the addition of workplace charging (the top right plot vs. the middle right plot in Figure 23), which is consistent with previous results showing only a few percent of vehicles parking at work on weekend days.

When charging at all other locations is added (the third row in Figure 23), the morning load peak increases further, but becomes broader. This is consistent with the explanation that people arrive at non-work destinations such as shopping or socializing at times that are not enforced and do not conform to rigid social norms. Early evening peak loads also increase slightly, and occur slightly earlier in the evening, as the load of people charging at shopping destinations, restaurants or alternative after work destinations is added to those of people parking at home. With each step of greater charging infrastructure, the load imposed on the grid by EVs in early morning hours is decreased, as they get more and more of their energy from daytime charging, immediately following travel throughout the day.

The effects of charging power on load shape, again assuming no active control, can be examined in greater detail by examining two specific battery sizes and a variety of charger sizes from the range of charging power examined. In Figure 24, grid load corresponding to homogeneous plug-in vehicle fleets consisting of vehicles with a large (52 kWh) and small (16 kWh) battery are mapped for charging infrastructure of 1, 2, 3.3, 9.6, 16.8, and 44 kW charging power, for each of the three charging infrastructure models. Note that while 44 kW charging was included in Figure 24, home charging at these levels is unlikely due to high marginal cost and low marginal utility to transportation of installing and wiring charging infrastructure beyond the power of other common household appliances. As in Figure 23, the data for each day were normalized by the number of vehicles in the study on that day, so the results are in units of kW of load per vehicle.

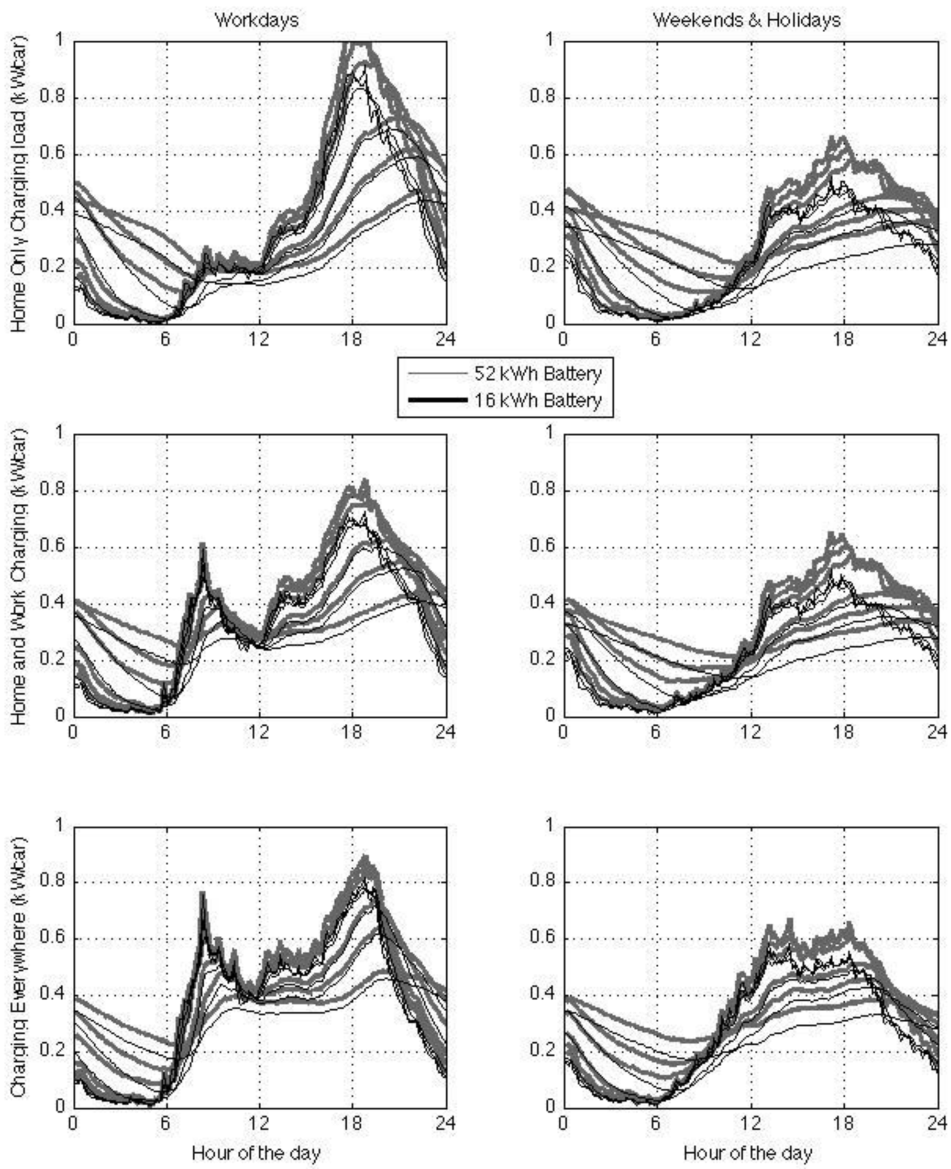

Figure 24: Grid load in kW per car through workdays and weekend/holidays, examining the effects of Plug Power for each of 16 and 52 kWh batteries. Charging load is plotted for 1, 2, 3.3, 9.6, 16.8, and 44 kW charging for each car.

From the load shapes in Figure 24 it is clear that higher power charging not only increases the height of the highest load peaks (i.e., increases maximum charging loads), but also displaces that load ‘backward’, or earlier in time. As was seen in Figure 23, lower power charging smooths load through the evening and night, by examining a greater range of charging power Figure 24 shows that this effect extends to the point that for the smallest chargers (120 V system chargers) load can still be a significant fraction of peak loads by the time vehicles start leaving for work the next day. This effect once again implies that not all vehicle batteries are full at the time of departure, which further implies an increase in trip failures for those vehicles. This corresponds to the significant decrease in trip success fraction at charging powers below about 6 kW, discussed in Chapter 6.

Figure 24 also shows that the effect on peak load due to increasing charger power rapidly diminish at higher powers; even though the progression of battery and plug sizes used in these analyses were roughly exponential, the peak loads they impose seem to approach convergence or asymptote beyond which further changes to load shape will be nearly impossible. This observation corresponds to the finding in Chapter 6 that above about 10 kW charging power, little marginal benefit in vehicle substitutability can be realized by additional charging power.

8.3 Utility and Grid Impacts

The results in the preceding section can be presented on the now-familiar axes of vehicle range and charging power by selecting only a single value from each of the curves of load through time. While assessing the load at some specific hour at which existing grid load is high would be useful, selecting any one representative grid load peak time would be disingenuous, as peak times change from one region to the next depending on the distribution of load types, and from one season to the next as heating and cooling loads alternate.

In the following three figures, the metric used to evaluate grid impacts is simply the magnitude of the evening peak load and the time during the day when that peak was reached. Thus the iso-graphic lines are lines of equal peak load (in kW per car) in the top plots, and lines of constant time (in 24-hour time) in the bottom plots. As before, since the model scenarios being evaluated relate to probable charging scenarios at home and at work, the results displayed are cropped to 20 kW, beyond which level the costs of installing home charging are likely to rise steeply, and the marginal benefit to vehicle users are negligible, as shown in Chapter 6.

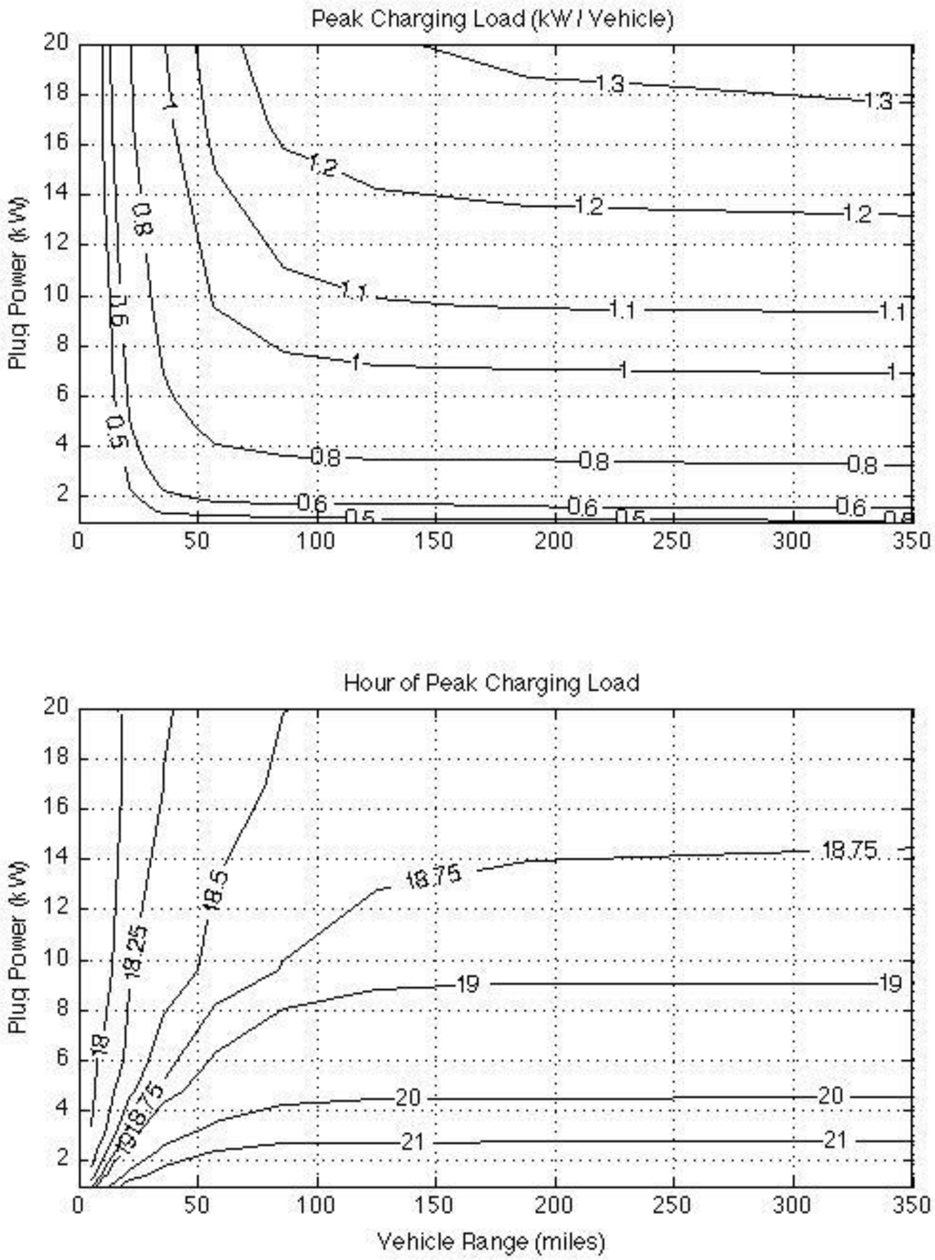

Figure 25: Grid load peak magnitude (top plot) and timing (bottom blow), charging at home only.

In Figure 25, the upper plot shows the average peak evening load, in kW per car, exhibited by a fleet of EVs of a given design. As an example to aid in interpretation, this data shows that a fleet of EVs with 80 miles of driving range (80 on the x-axis), that plug into 8 kW plugs at home parking locations only (8 on the y-axis) would impose an average evening peak load of approximately 1 kW per vehicle. The lower plot in Figure 25 shows the time at which these peak charging loads occur. Using the same example, a fleet of 80-mile EV plugging into 8 kW chargers at their respective home locations puts the peak load at 1900, or 7pm.

Many of the patterns discussed in section 8.2 can be seen with greater clarity in this figure: As charging power available at home is increased (moving up in the plot), peak loads are always increased, and the hour at which that peak occurs moves to earlier in the evening. As noted in section 8.2 however, the increase in load peak is far less than linearly proportional to the charging power of each vehicle. Also of note is the fact that the effect on the hour of load peak (bottom plot in Figure 25) is much more dramatic for vehicles with small batteries, for vehicles with batteries that provide more than about 100 or 150 miles of range, very little shift in load peak timing occurs above 16 kW charging power.

By adding work charging, the load peak and peak time change as shown in Figure 26.

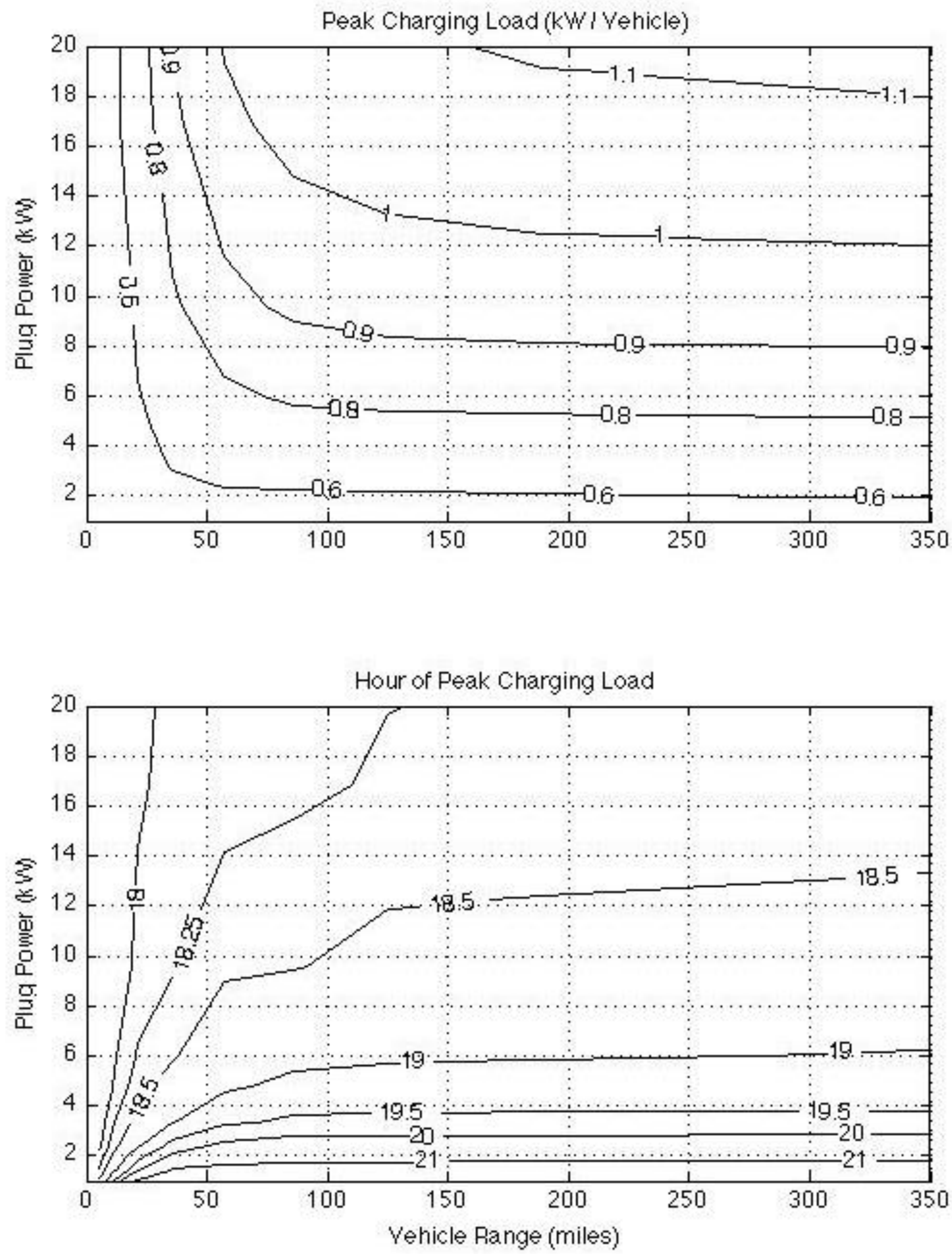

Figure 26: Grid load peak magnitude (top plot) and timing (bottom plot), charging at home and work.

Two interesting observations can be seen in Figure 26, that once again corroborate and refine the observations made in the preceding section: Because charging at work puts at least some energy into the batteries of the fleet of vehicles, less is needed at home in the evening, so peak loads for all vehicle configurations are reduced. (The added loads imposed by vehicles charging at work are for the most part non-coincident with the loads of vehicles charging at home). The second observation that may be drawn from Figure 26 is that, compared to the 'home only' charging scenario depicted in Figure 25, charging load peaks arrive earlier in the evening for all vehicle configurations. This can similarly be attributed to cars arriving home with more energy remaining in their batteries; for any given battery size and charging rate it therefore takes less time to fill the battery's 'empty space', so for each car that charged at work, evening at-home charging is completed sooner, so fleetwide evening charging loads begin to taper off sooner.

By adding charging at all parking locations where vehicles stop for 30 minutes or more, peak loads and peak load timing again changes, as shown in Figure 27.

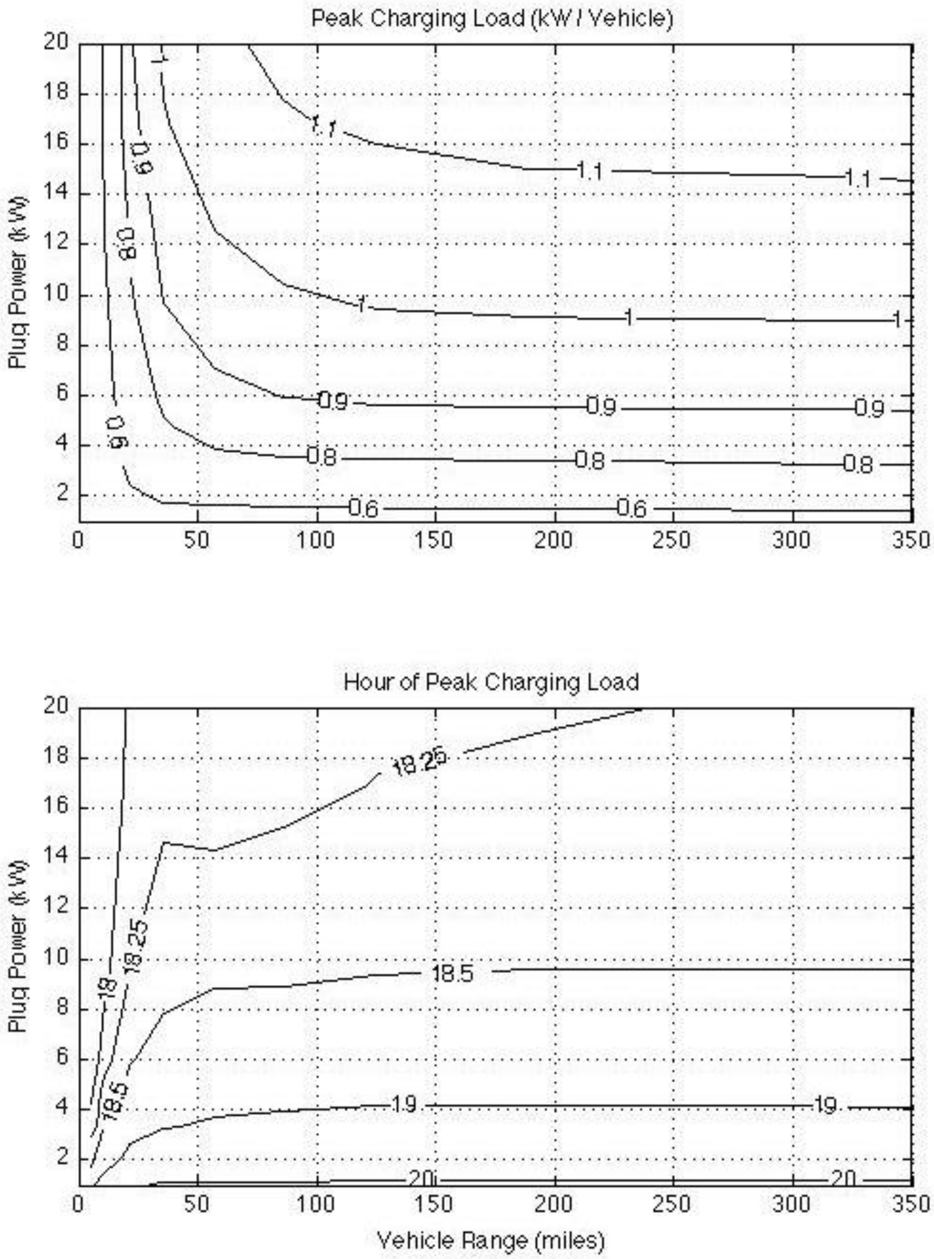

Figure 27: Grid load peak magnitude (top plot) and timing (bottom plot), charging everywhere.

Comparing Figure 27 to Figure 26 shows the same pattern of changes in peak load timing seen in comparing Figure 26 to Figure 25, but reverses the trend in load peak magnitudes. Because alternate evening destinations now have charging, the peak loads increase again relative to the home &work only case, though are not as high as in the home charging only case. As before, additional charging locations makes the peak load appear earlier in the evening, as vehicles arrive at charging locations with more energy left in their batteries, so complete their evening charging sooner.

Thus, from this section the following general rules can be drawn: i) Adding charging infrastructure beyond 'home' locations, the magnitudes of evening peak loads and the change in timing of those peaks depends on where those added charging opportunities are; charging at work, or daytime parking locations that are unlikely to be frequented after business hours reduces evening charging loads, while providing charging at evening entertainment destinations increases evening loads. ii) Larger batteries and smaller plugs both contribute to postponing the load peak. iii) Smaller batteries and smaller plugs both contribute to decreasing the magnitude of the load peak. Thus the interests of the utility and the interests of the vehicle owners are, at least in this combination of scenarios, in conflict. In the next sections a mechanism to align the interests of utilities and vehicle owners will be explored.

8.4 The Importance of Charging Algorithm to Vehicle Substitutability and Grid Load

When and how quickly an electric vehicle charges could have dramatic effect on its ability to provide transportation services, and aggregated over a fleet could likewise have a great effect on the impacts of EV charging on load. Charging algorithm, i.e. strategies for the timing and rate at which vehicles absorb energy from the grid, are therefore a very important component of an analysis of grid impacts. In the previous section, I analyzed the effect on load when there was no active algorithm at all. In this section and the next, eleven charging algorithms are examined that differ in when the battery may be charged, how fast it may be charged (*i.e.* how much power should be drawn from the grid), and in a target state of charge of the battery. The algorithms can be grouped into four classifications based the information used to control charging. The first classification uses no information, and simply charges when the vehicle is plugged in (as was the case in the prior section), the second classification uses only the time of day as a proxy for information about the needs of the electrical grid, while the third and forth classes use information about the driving habits and travel needs of the vehicle owner.

The first 'class' of algorithms consists of only one algorithm; the one used in the preceding chapters. It has been described as 'dumb charging' and 'simple charging' and mimics the actions of most plug-in devices:

- Algorithm 1 is "Charge Right Away", and reproduces the effects of 'simple' or non-responsive charging. The vehicle simply charges as soon as it is plugged in (as soon as the trip is over in the travel model), and charges at the maximum rate possible until the battery is full or the next trip begins.

The second set of algorithms represents efforts to compensate for daily fluctuations in electrical grid loading, and so varies charging behavior based on the time of day. This algorithm might be implemented in areas with 'time-of-day' or 'time-of-use' energy pricing, wherein electricity is priced differently based on the specific hour of the day in which it is drawn from the grid. Three charging algorithms are tested that treat daytime (defined in this study as 6 am – 11 pm) and nighttime (11 pm – 6am) differently.

- Algorithm 2 is "Charge Only at Night", and charges the car only between the hours of 11 pm and 6 am, but does so at the maximum rate possible.

- Algorithm 3 is "Charge at Half Rate During Day". It allows the car to charge at half of the maximum rate during the day, defined for each travel model by the charging power parameter, and at the full rate between 11 pm and 6 am.

- Algorithm 4 is "Charge to Half Battery During Day", which charges the battery only up to half of its maximum energy capacity during the day, defined by the battery size (proportional to the vehicle range parameter in the travel model), charging above half charge only 11 pm to 6 am.

The next set of charging algorithms assume knowledge of upcoming trips, and put just enough energy into the battery to address upcoming needs, plus a range buffer. This methodology reflects efforts currently underway to devise learning software that allows the vehicle to make predictions about when and how long the next trip will be (Kamboj et al. 2010), or equivalently from the perspective of the algorithm, simply requiring that the driver enter future trips into a schedule.

- Algorithm 5 & 6 charge the battery at the maximum rate 'At the Last Minute', such that it reaches the charge necessary for the upcoming trip exactly when that trip starts. Also, as soon as the vehicle is plugged in, these algorithm will insure at least a range buffer of 10% (in Algorithm 5) or a range buffer of 25% (in Algorithm 6) of the battery capacity, The charging is done just in time for the start of that trip. Due to the range buffers specified and the "just enough for next trip' and "last minute" rules, these algorithms maintain the battery at 10% or 25% charge most of the time.

- Algorithm 7 & 8 charge the batteries at a constant rate while the vehicle is plugged in, usually at less than the maximum possible rate, with the same goal of arriving at 'just enough' charge (plus 10% or 25% of battery capacity, respectively) 'Just in Time'.

A final three algorithms are composites of "Simple Charging" and the predictive algorithms in the third set.

- Algorithm 9 is called "Full Each Morning, Incidental for Trips". It begins charging after the last trip of the day, and charges at full power until daytime electric rates kick in at 6 am, until the battery is full, or until the first trip of the next day begins, whichever comes first. During the day, the predictive ability assumed for the third set of charging algorithms provides incidental charging for upcoming trips when needed.

- Algorithm 10 is the same as Algorithm 9, but a 10% range buffer added to the daytime predicted charge need.

- Algorithm 11, "Charge When Needed", reflects observed EV driver behavior; many drivers do not charge, even when charging is available and off-peak, if they can complete their upcoming travel with the existing stored energy. This algorithm looks ahead and charges only when the sum of trip distances in the next 24 hours exceed remaining range. When it does charge, it charges at full rate and until full (or until the next trip starts).

These prescribed algorithms will not perfectly represent the complex interaction between an electric vehicle operator, the remaining range or state of charge, and the available charging infrastructure. Rather, comparing them helps to identify the parameters that must be traded against one another, and the relative effects on the vehicle's service to the vehicle owner, and on the loads on the grid.

8.5 Success in Travel Services vs. Charging Algorithm

The vehicle serviceability effects of charging infrastructure were explored in Chapter 6. Before looking at the effects on grid loading of the eleven charging algorithms discussed in section 8.4, it seems prudent to evaluate them by the Adaptation Days metric used previously. The results of the substitutability analysis, using the same procedures described in Chapters 6 and 7, examining different charging algorithms are presented in Table 10. At home charging is evaluated for the same 8 representative vehicles used throughout this research. To ease formatting, each of the vehicles is described in a column, while each of the charging algorithms is a row.

Table 10: Comparison of Adaptation Days necessary for 8 sample vehicles using each of the charging algorithms, charging at "Home" only.

Similar To		*Tesla S*	*Tesla S*	*Tesla S*	*Tesla S*	*Tesla S*	*Tesla S*	Nissan Leaf	Chevy Volt
Range	*(Miles)*	*143*	*143*	*143*	*306*	*306*	*306*	*86*	*37*
Charging	*(kW)*	*3.3*	*9.6*	*18*	*3.3*	*9.6*	*18*	*3.3*	*2*
Alg. 1	*(Days)*	11	9.4	9.1	3.9	3.2	3.1	25.4	94.3
Alg. 2	*(Days)*	21.2	15.3	15.2	11.1	5	4.8	37.8	118.4
Alg. 3	*(Days)*	12.9	10.1	9.5	5	3.4	3.2	28.2	100
Alg. 4	*(Days)*	13.5	11.4	11.1	4.9	3.6	3.5	30.1	108.1
Alg. 5	*(Days)*	15.4	10.9	9.7	9.3	4.8	3.8	28.3	95.8
Alg. 6	*(Days)*	12.9	10	9.3	6.1	3.8	3.4	26.7	94.9
Alg. 7	*(Days)*	15.4	10.9	9.7	9.3	4.8	3.8	28.3	95.8
Alg. 8	*(Days)*	12.9	10	9.3	6.1	3.8	3.4	26.7	94.9
Alg. 9	*(Days)*	14.3	13.1	12.9	5.1	4.3	4.2	32.6	110.1
Alg. 10	*(Days)*	11.7	9.8	9.2	4.2	3.3	3.1	26.5	96
Alg. 11	*(Days)*	16.9	14.5	13.9	8.8	6.1	5.7	32.1	100.1

Table 10 shows that several of the charging algorithms, notably 3, 6, 8 and 10, impose very little penalty on vehicle utility compared to the baseline and most aggressive case of Algorithm 1 (Charge Right Away). It seems reasonable to expect that these penalties would be even smaller if the human intelligence of a driver were applied to adjusting charging behavior on a day-by-day or trip-by-trip basis. Using this assumption modifies the implication of these results, or possibly the meaning of the term 'adaptation days' to include days on which the vehicle owner would have to modify or over-ride the default charging algorithm to insure that the car is adequately charged to meet upcoming travel needs. As with other adaptations (discussed in Chapters 5 and 6), this adaptation would not be particularly onerous or burdensome to the vehicle owner, provided she had adequate knowledge of upcoming trips (a requirement of adaptation to limited travel range), and controls and systems were in place on the vehicle to facilitate such charging algorithm modification.

It should be noted that without appropriate incentive structures in place, the owners of electric vehicles have little or no motivation to opt for any charging algorithm other than the simple case of "Charge Right Away" (Alg. 1), which, as Table 10 shows, will always result in the least driver inconvenience, because it always produces the highest state of charge for any given pattern of driving and charging. A simple policy mechanism for diverting load to times of lower system-wide electricity usage, one already in place in many electrical jurisdictions, can be accomplished, for example, by charging a higher rate for electricity consumed during peak hours than electricity consumed during off-peak hours. This practice is often referred to as 'time-of-use' rates, or 'peak pricing'. In the charging algorithms investigated, which generally are designed to shift charging power draw to overnight hours, the potential remuneration to vehicle owners thus already exists in the many electrical distribution jurisdictions that have such rate structures in place.

8.6 Effect of Charging Algorithm on Daily Load Profile

As before, the base case will be taken as a driver who charges at Home only, and who employs 'dumb' charging, i.e. charging at maximum rate immediately upon plugging in. Due to the construction of the model, it should be noted that this driver plugs in and charges at every parking event at Home lasting more than 30 minutes. In reality, even in the absence of electrical rate structures to discourage peak-coincident load, some charging opportunities may be ignored or foregone if the driver knows that more than enough range remains in the battery to complete the next trip, a behavior around which the design of Algorithm 11 is based.

8.6.1 Base Case: Charge Right Away (Home Only)

The effects of unconstrained charging at home may be assumed to be, in simplified terms, a function of the change in the population of vehicles that is parked at home, which are shown in Figure 28, and the *rate* at which vehicles arrive at charging locations. This relationship can be seen from comparing Figure 28 and Figure 29. Figure 28 is a reprint of Figure 2, presented here for context, while Figure 29 presents the same data provided in the first set of plots from Figure 23.

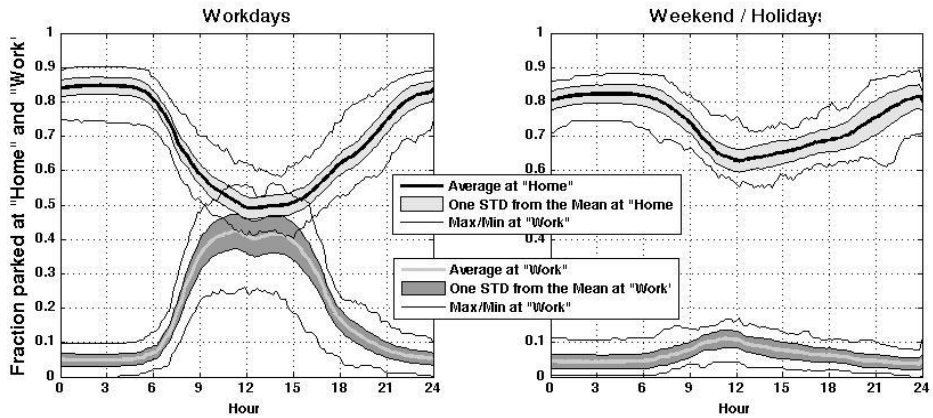

Figure 28: Fraction of vehicle fleet parked at Home and at Work through time.

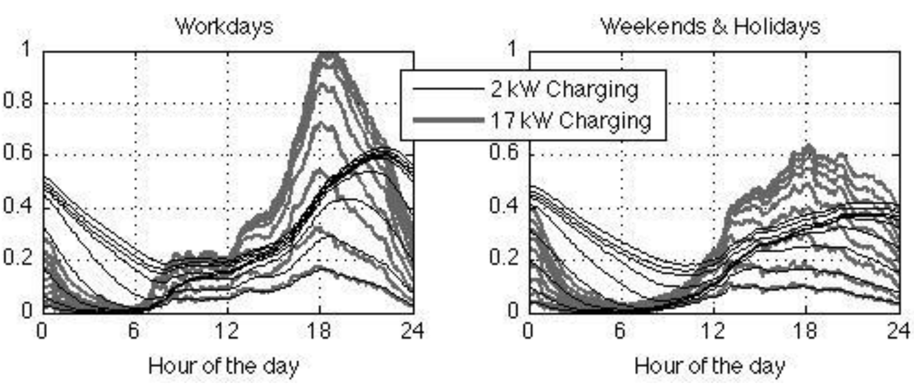

Figure 29: Grid loading for 1.5, 3, 6, 10, 16, 24, 35, 53 and 100 kWh battery sizes charging at Home only at 1.9kW (black lines) or 16.8kW (grey lines). Load is kW per vehicle throughout the day.

Note again that in Figure 29 two values of vehicle charging power are described, each by 9 lines (grey and black respectively) representing different vehicle battery capacities. These are 1.5, 3, 6, 10, 16, 24, 35, 53 and 100 kWh batteries. While presenting this much information does make it hard to pick out specific individual results from the graphs, it shows the trends that result from more variables than a 2-dimensional plot can otherwise describe. In the analysis presented in section 8.2, the information in Figure 29 was the base point for an investigation of the effect of adding charging infrastructure to locations other than each vehicle's Home. In this section, the Home only charging grid impacts produced from 'charging right away' (Algorithm 1) are presented as the base point for an analysis of different charging algorithms.

8.6.2 Second Group; Application of Time of Day Information

The second set of charging algorithms, presented in section 8.4, use the time of day as a trigger for various charging behaviors. The grid loadings resulting from Algorithm 2 'Only at Night', Algorithm 3, 'Half Rate During the Day', and Algorithm 4 'To Half Full During the Day' can be seen below in Figure 30, as successive pairs of weekday (left column) and weekend day (right column) plots. As in Figure 29, Figure 30 shows the grid load resulting from each of 9 sizes of batteries for each of two charging powers.

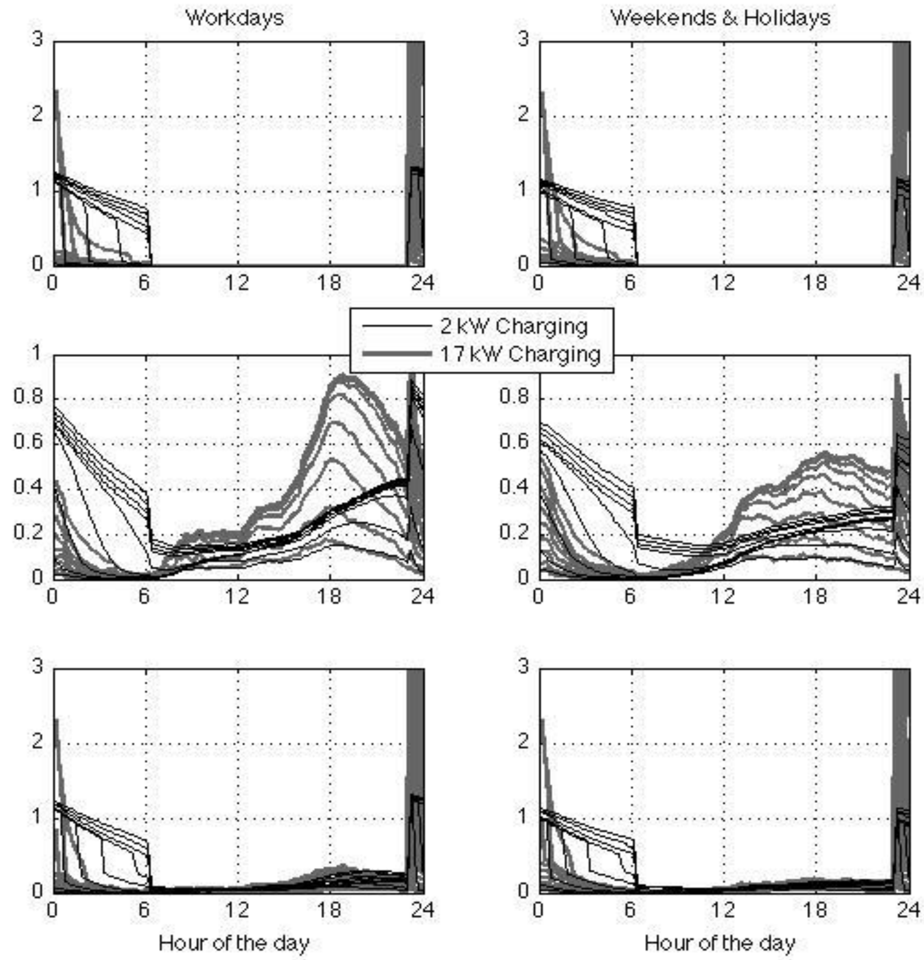

Figure 30: Charging Algorithm Group 2; Charge only at night (top), Charge at half rate during day (middle), and charge to half battery during day (bottom). Grid loading for 1.5, 3, 6, 10, 16, 24, 35, 53 and 100 kWh battery sizes on workdays (left) and weekends and holidays (right).

The effect of time-sensitive charging is evident throughout Figure 30. The most dramatic of these effects is the spike in load at 11pm, when vehicle switch from their daytime behavior to their nighttime behavior. Note that in the top set of plots (Algorithm 2, charge only at night) and the bottom set (Algorithm 4, charge to half full during the day), the y-axis scale of the plots have been expanded significantly to show more of this spike. The resulting load curves, while still exceeding the plotted range, show that average grid loads spike as high as 11 kW per vehicle (based on 16.8 kW charging power). For real system applications of these algorithms, it would be essential to incorporate some randomization or staggering of this state transition, to avoid this large load spike.

In the morning, when nighttime behavior transitions to daytime behavior at 6am (as defined in the charging algorithms), certain combinations of large batteries and low power chargers likewise experience a steep drop in charging load. While very small batteries exhibit little of the effect, as batteries become large enough that seven hours of charging overnight is insufficient to completely fill them, the drop in power draw at 6 am is distinct.

Comparing the cases of ‘Charge at Half Rate’ (middle plots) to the base case ‘Charge right away’ in Figure 29, it is interesting to note that very little reduction of aggregate load is realized. This can be explained as the effect of vehicles charging for longer, and system wide loads accumulating among a larger fraction of the fleet compensating for lower loads in each charging vehicle. The largest evening peaks in the ‘Charge at Half Rate’ case are indeed only about 20% lower than the corresponding peaks for unconstrained charging shown in Figure 29, despite the power draws of individual vehicles being definitely 50% lower.

8.6.3 Third Group; Use Knowledge of Upcoming trips

The third set consists of four charging algorithms that use knowledge of upcoming trips as a signal for when and how fast to charge. Battery energy buffers of 10% and 25% of battery capacity are used. These buffers mean that the batteries respond to conditions as though the 'first' 10% and 25% of their energy capacities were not there. For example, in a 40 kWh battery with a 25% energy buffer, if 4 kWh is needed for an upcoming trip, the battery would attempt to charge to 14 kWh for that trip (a 10 kWh buffer + 4 kWh for the trip). Initial attempts at implementing these algorithms did not include any battery energy buffer level, and proved excessively deleterious to adaptation day counts. Because the algorithms only look forward to the next trip, with no buffer, the parking duration before longer trips was often insufficient to prepare for that trip. Related findings, referring specifically to charging time prior to longer trips (150 miles or more), were described in section 7.2 and shown in Figure 18.

The grid loadings resulting from Algorithms 5 and 6 'At the Last Minute', with 10% and 25% battery energy buffer, respectively, and Algorithms 7 and 8 'At a constant Rate', likewise with 10% and 25% battery energy buffer, are presented below in Figure 31. As before, they are presented as successive pairs of weekday (left column) and weekend or holiday (right column) plots. As in the previous figures of this format,

Figure 31 shows the grid load resulting from each of 9 sizes of batteries (1.5, 3, 6, 10, 16, 24, 35, 53 and 100 kWh batteries) for each of two charging powers (2 and 17 kW).

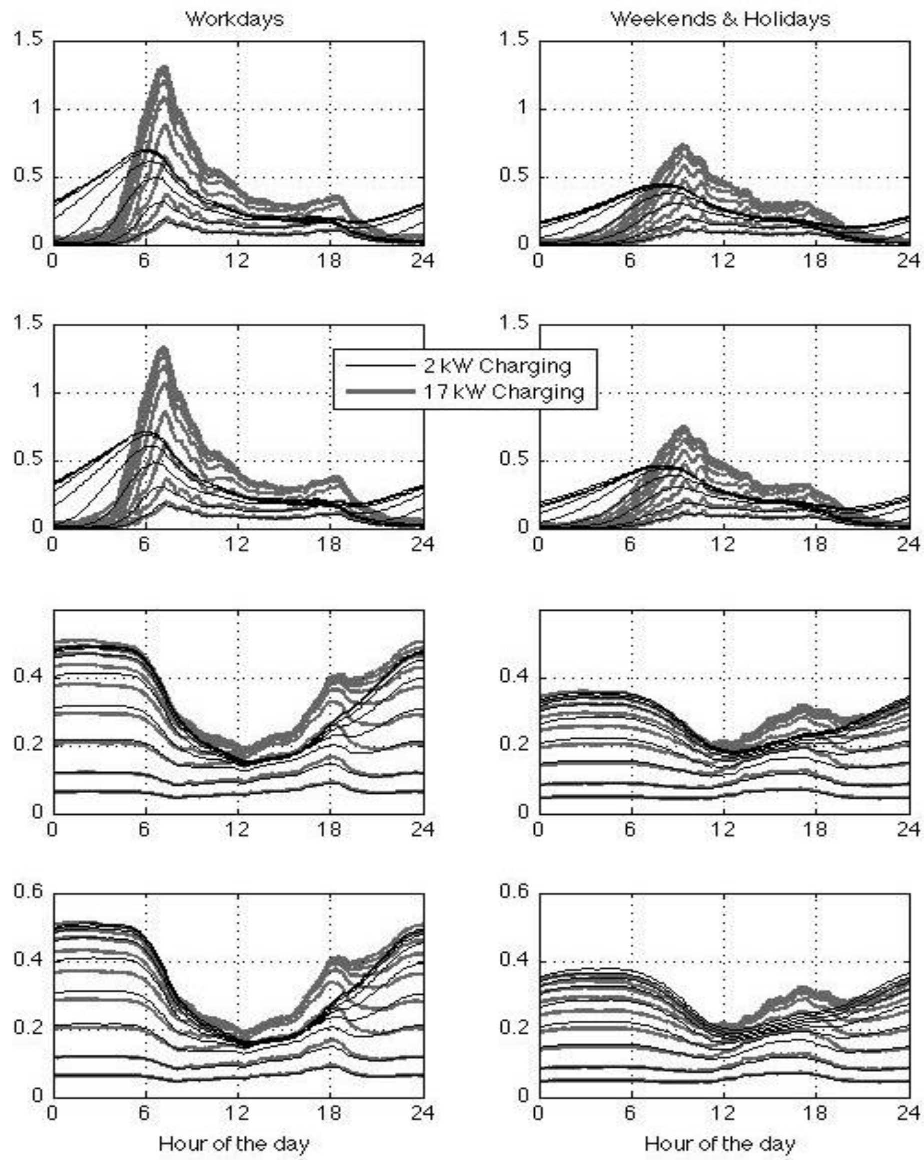

Figure 31: Charging 'At the Last Minute' and 'At Constant Rate' to be ready for upcoming trips from home only. 1.5, 3, 6, 10, 16, 24, 35, 53 and 100 kWh battery sizes. The first and third pairs represents a 10% of battery energy buffer, the second and forth pairs represent a 25% energy buffer.

The upper two rows of plots in Figure 32, which show the grid loading that results from charging 'At the Last Minute', clearly show a spike in load preceding the principle times of vehicle departure from home. Unsurprisingly, higher power charging (grey lines) result in higher grid loads, while lower power charging (black lines) extend grid load backwards in time, as batteries must start charging earlier to get to the necessary state of charge for a given trip.

In contrast to this, charging at a constant rate in preparation for upcoming trips, shown in the lower two sets of plots in Figure 31, results in a power draw curve that looks remarkable like the curve of fleet fraction at home through time shown in Figure 28. Even for the largest battery sizes examined, grid loads resulting from charging at a constant rate to prepare for upcoming trips never exceeds 500 W per car, and is much lower during what in many electrical jurisdictions are the hours of greatest grid loading, from 6 am to 6pm. Such a power draw would be, in almost all electrical jurisdictions, of little impact to existing capacity constraints, and would almost certainly be very attractive to distribution system managers.

Another very significant observation about these pairs of plots is that Algorithms 5 and 6 (the upper two sets of plots) are very similar, to the point that without doing a numerical analysis it is difficult to pick out any differences at all. The same is true for Algorithms 7 and 8 (the lower two sets of plots). The significance of this fact relates back to the Adaptation day results presented in Table 10, which showed significant improvements in vehicle substitutability resulting from the modest increase in battery energy buffer levels from 10% to 25%. If improvements in vehicle substitutability can be realized with little or no penalty in grid load, a clear direction in charging strategy is made evident.

8.6.4 Forth Group; Emulate Driver Intelligence or Driver behavior.

The fourth set of charging algorithms attempt to emulate more realistic EV driver behavior. This group contains three algorithms that regulate charging through the use of a combination of time of day information and knowledge of upcoming trips. The grid loadings resulting from Algorithms 9 and 10 ‘Full Each Morning, Incidental for Trips’, with 0% and 10% battery energy buffer, respectively, and Algorithm 11 ‘When Needed’, are presented below in Figure 32. Plot formatting is the same as it was for the figures in the rest of this section.

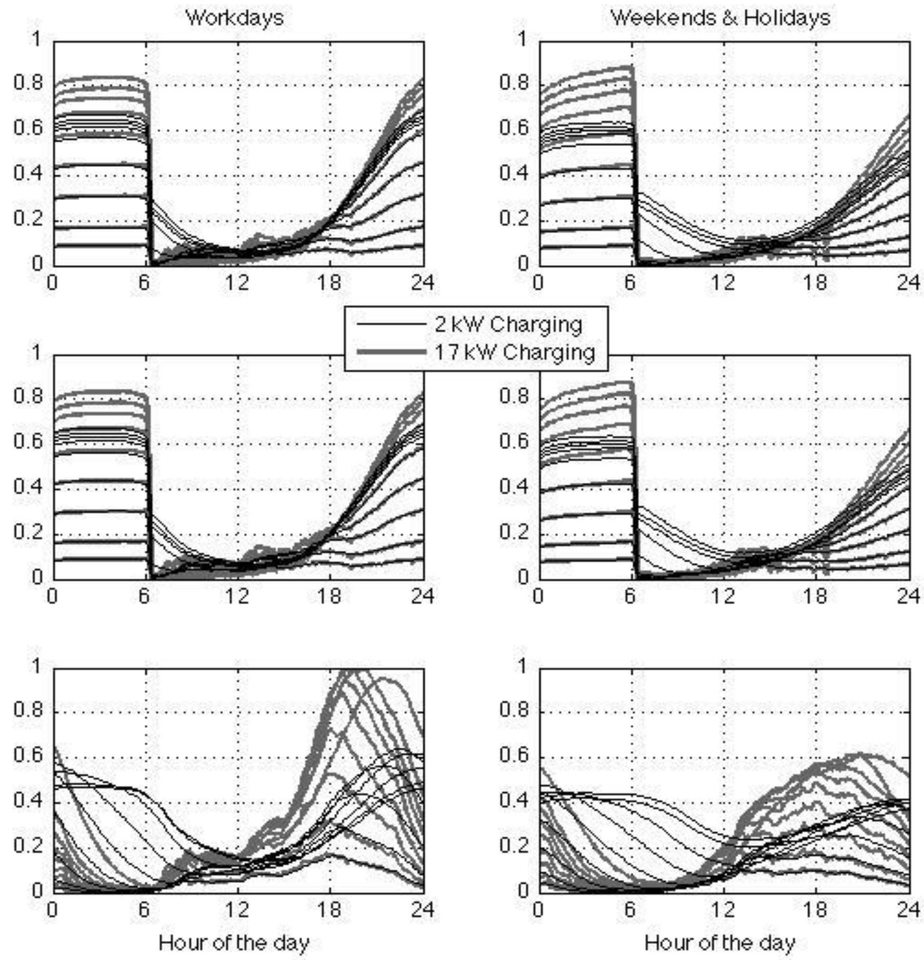

Figure 32: Grid load through time resulting from charging to be 'Full Each Morning' (top), or 'Full Each Morning with 10% battery buffer' (middle), and Charge for the next day's trips (bottom). Curves show high power (17 kW) and low power (2 kW) charging of 1.5, 3, 6, 10, 16, 24, 35, 53 and 100 kWh batteries at home only.

In Figure 32, the same absence of significant effect from a battery energy buffer, noted when comparing Algorithm 5 to Algorithm 6, and Algorithm 7 to Algorithm 8, can also be seen when comparing Algorithm 9 to Algorithm 10. The high grid loading through the night and negligible load during the day likewise make this algorithm of interest from the perspective of grid management. In that regard it may be even better than Algorithms 7 and 8 shown in Figure 31, since loads are higher at night and lower during the day, and the period of low load lasts later into the evening.

The final algorithm assessed, Algorithm 11 'Charge only when needed' for upcoming trips, is remarkable in its similarity to Algorithm 1, 'Charge right away'. The reason for this is related to the nature of aggregated load: Each vehicle looks ahead at 24 hours' of travel, and charges only when that travel exceeds its current remaining range. While each vehicle individually will present a highly variable charging load, as load is aggregated throughout the fleet, the timing of charging becomes a function of the fraction of vehicles at charging infrastructure, and the rate at which vehicles arrive at infrastructure, just like Algorithm 1. Because in Algorithm 11, when vehicles do charge, it is in the same manner as Algorithm 1, specifically i) as soon as they plug in and ii) at full power rate until the battery is full or the next trip starts, the aggregated load curves are very similar.

8.7 Comparing peak loads to adaptation days

One important potential consequence of this research is the development or design of charging systems and algorithms that minimize both the loss of vehicle utility and grid impacts due to added peak-coincident loads. Because it is not possible to say what the relative value of those two parameters will be for any given electrical system or EV driving population, the impacts must be compared in a general form.

In developing a single value for grid load impacts that can be attributed to a given vehicle configuration and charging algorithm, several possible parameters could be used with equal validity. The previously discussed fact that load peaks do not happen at the same time of day in all jurisdictions or in all seasons makes any one metric non-universal, yet trying to show all effects for all electrical systems would be futile. The parameter used in the following analysis is the root mean squared (RMS) load added to the system by vehicle charging between the hours of 2pm and 7pm, inclusive. The RMS value will increase the impact of higher load peaks on the assessed metric. Load is calculated at 10-minute increments, so 31 time points are assessed. Those 5 hours capture the worst loads in most jurisdictions, but not all. Extending the time span examined would make the results applicable to more distribution systems, but would decrease the specificity of the results to all. Thus it must be emphasized that this parameterization of grid impacts is neither universally representative (because of different electrical system configurations), nor precise (because of inter-day variability of the fleet driving patterns), but may hopefully serve as a broadly applicable general characterization.

In Figure 33, the grid impacts and Adaptation Day count impacts of the 11 charging algorithms investigated in this section are plotted for a fleet of EVs with the characteristics and capacities of a 2011 Nissan Leaf; a 24 kWh battery and the ability to charge at 3.3 kW. The x-axis of the plot is the RMS charging load of the vehicle fleet between 2 and 7 pm, while the y-axis is the average Adaptation day count among the fleet.

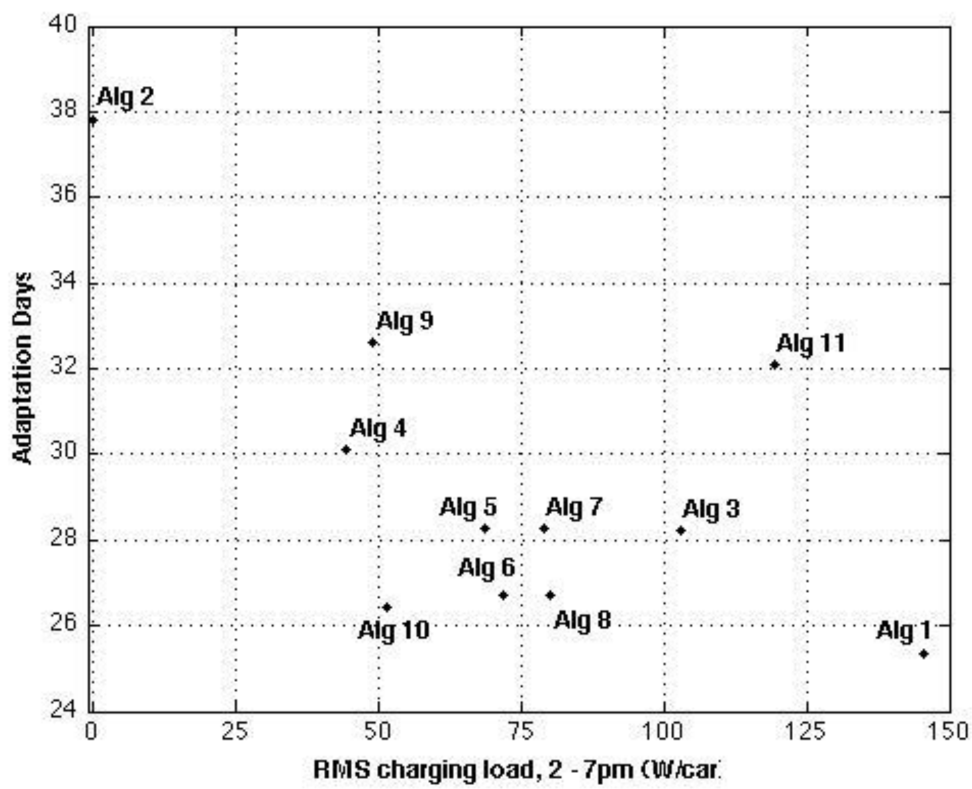

Figure 33: The effect of the 11 prescribed Charging Algorithms on RMS peak-coincident grid load and on Adaptation Days for a Nissan Leaf-like vehicle.

From Figure 33 it is clear that, as previously discussed, Charging Algorithm 1 'Charge Right Away' will always produce the highest state of charge of the battery, and thus the fewest adaptation days, thus the mark labeled "Alg 1" is lower than any of the others at just over 25 days. Here we see that for a Leaf-like vehicle, it also produces the worst grid loads, and is thus the farthest right on the plot at almost 150 W per vehicle. In contrast, Algorithm 2 'Charge Only at Night' while by definition can never impose any charging load between 2 and 7pm, results in the greatest number of adaptation days among algorithms at almost 38 per year, but no grid impacts at all (by this metric). The other algorithms are arrayed between these two extremes. The relative merit of these other algorithms can be evaluated (again, for a 24 kWh EV charging at 3.3 kW at home only), by their proximity to the bottom left corner of the plot, where both grid impacts and driver inconvenience are minimized.

From the results shown in Figure 33 it seems that for a Leaf-like vehicle Algorithm 10, which charges at full power from the last trip of the evening until 6am, and then spot charges during the day when necessary to maintain a 10% battery energy buffer, seems hard to beat. It is plausible, however, that different vehicle configurations will respond differently to the various algorithms. To investigate this, the multiple configurations of Tesla Model S used previously as benchmark points of analysis are again evaluated and plotted on the same graph. In order to simultaneously see the effects of changing battery capacity and changing charging power, multiple vehicle configurations are plotted together, with the individual points of each being connected by line segments. These results are presented in Figure 34. Note that neither x-axis nor y-axis scales are held constant between plots within Figure 34. In the top two plots of Figure 34, charging power is varied for Tesla Model S configurations with fixed battery capacity (40 kWh in the top left plot, 85 kWh in the top right plot), while in the bottom two plots, battery power is varied for vehicle configurations with specific charging powers (3.3 kW in the bottom left plot, 18 kW in the bottom right plot).

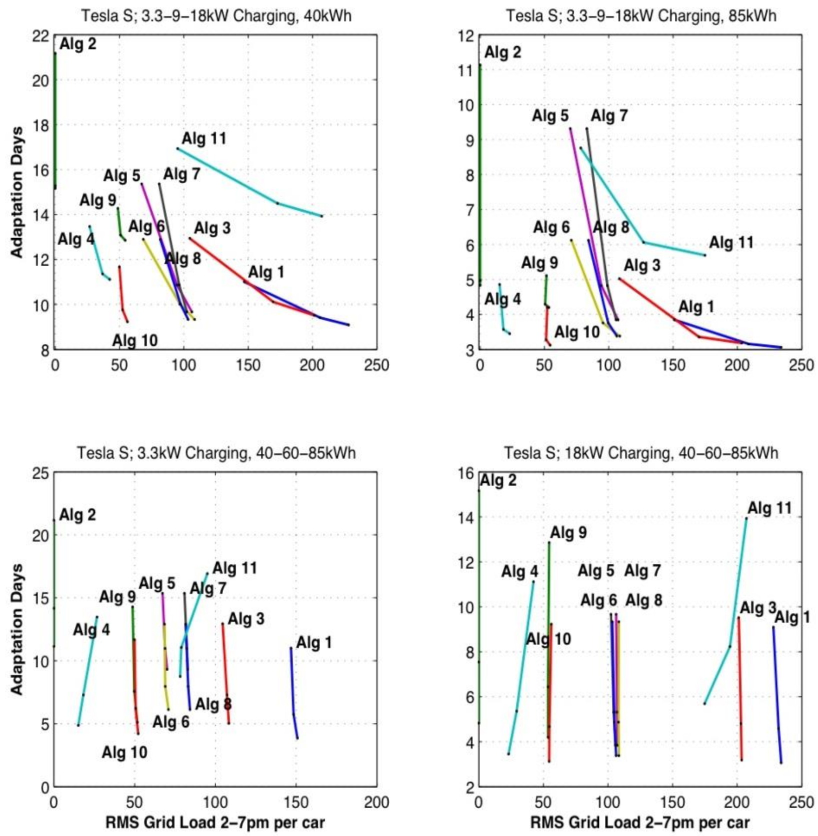

Figure 34: Relationship between grid loading and Adaptation days caused by 11 charging algorithms, for various configurations of Tesla Model S-like vehicles.

Four subplots are presented in Figure 34. In the top two of these, results of the analysis of the effects of both charging algorithm choice (by the distinct lines) and charging power (by the points on each line) are presented. In the bottom two plots, each line again represents one charging algorithm, but the points on the lines indicate different battery sizes. In the left two plots, the lower range of battery size and charging power (respectively) available to a hypothetical Tesla Model S buyer are assessed, while in the right two plots the higher respective values are evaluated.

In the top left plot of Figure 34, the Adaptation Days and RMS grid load between 2 and 7pm are plotted for EVs with 40 kWh batteries that charge at home only, at charging powers of 3.3 kW, 9 kW, and 18 kW. For each algorithm there is therefore a line connecting three vehicle configurations, corresponding to three charging powers. In all cases, the higher the charging power, the smaller the number of adaptation days, so each algorithm-specific line should be read as sinking down (and to the right on the top left plot) as charging powers increase.

Several interesting observations result from the analysis presented in Figure 34. Foremost among these is that while increasing the charging rate (following each line down in the top two plots) universally increases grid loading, in some cases significantly, increasing battery size (following each line down in the bottom two plots) can actually decrease grid loads during the definitional peak hours of 2pm to 7pm, while at worst, increases in grid load are dwarfed by decrease in adaptation days (indicated by nearly vertical lines in the bottom two plots). While counterintuitive, this effect is the case for Algorithm 4, which ceases daytime charging once the battery reaches half full, and Algorithm 11, which charges regardless of time, but only when upcoming trips require additional energy. It must be concluded that both of these algorithms preferentially put more energy into the battery during off-peak hours (defined as between 7 pm and 2 pm for this analysis), and as battery capacity increases, the need for on-peak charging falls.

It is also interesting to note that the four algorithms that base charging on the needs of the next trip, Algorithms 5 – 8, converge in their effects on vehicle substitutability and on grid impacts as vehicles charging rates increase, though unsurprisingly, a greater battery energy buffer level (Algorithm 6 & 8) persistently reduces adaptation days. Similarly, the relative merits of Algorithm 4 'charge until half full' improve as battery sizes increase. For Nissan Leaf-like vehicles, Algorithm 10 (overnight charging with spot charging during the day to maintain a 10% buffer, shown in Figure 33) is unambiguously superior. However, the lowest point on the Algorithm 4 lines in the three plots of Figure 34 that include an 85kWh battery suggest that, while still necessitating more adaptation days than charging algorithm 10, algorithm 4 offers a significant potential reduction in peak grid loading, such that the relative values of optimizing the two metrics must be carefully weighed against each other in a given use case, travel pattern, or electrical jurisdiction to select which might be preferable.

Chapter 9

GRID-INTERACTIVE VEHICLES; EVALUATION OF A DISTRIBUTED STORAGE RESOURCES

Grid interactive vehicles and V2G capable vehicles can serve as a managed load or distributed storage resource for the electrical system. In this chapter the magnitude of that resource will be evaluated. In addition, the effects of each of the variables investigated throughout this research—battery size, charging power, charging infrastructure availability, and charging algorithm—will be assessed. Section 9.1 will introduce and explain some of the differences between grid services, and give additional background to the field of grid interactive vehicles and V2G. In Section 9.2, analytical solutions and relationships between various vehicle use parameters, vehicle capacities, and the services they can provide are developed. In Section 9.3 the principle uncontrolled variable informing the results of the previous section, namely the amount of time vehicles spend plugged in, is explored based on the Commute Atlanta data. Section 9.4 examines how vehicle design, consisting of battery size and charging power affects its ability to provide capacity-based grid services. Finally, in Section 9.5, the intra-day fluctuations in the quantity of energy available online from GIVs are examined.

9.1 Background

Grid-interactive vehicles (GIVs) are plug-in vehicles that can adjust the amount of power flowing between the grid and the vehicle, based on a signal from an external entity. The signal can be a command, a request, or less directive information such as a market price, or a combination of such information. The signal will in most cases be derived from the quasi-instantaneous conditions on the grid (Stark et al. 2009, Kempton et al. 2012). By responding to these commands, the batteries in such vehicles can be made to act as a grid-connected managed load or storage resource, and by responding appropriately to the signal, the vehicles can perform electrical system stabilizing services that have value to the electrical system (Lachs, Sutanto & Logothetis 1996, Sutanto 2004, Kempton, Tomić 2005b, Tomić, Kempton 2007). Among grid-interactive vehicles, some can do more than just modulate charging load on command, specifically, some can also send power back to the grid, from the battery, through the charging infrastructure. (No such vehicles are in mass production, though they are available via custom build). These vehicles, and the additional services they can perform, are called Vehicle-to-Grid, or V2G (Kempton, Letendre 1997, Kempton, Kubo 2000).

The concept of V2G has been in development since the late 1990's by a number of individuals and institutions, most notably Prof. Willett Kempton at the University of Delaware (Sutanto 2004, Kempton, Tomić 2005b, Tomić, Kempton 2007, Kempton, Letendre 1997, Kempton, Kubo 2000, Kempton et al. 2001, Kempton, Tomić 2005a, Guille, Gross 2008, Andersen, Mathews & Rask 2009, Sovacool, Hirsh 2009, Sovacool, Hirsh 2009, De Los Ríos et al. 2010). In board strokes, the principle is that plug-in vehicles, when their stored on-board energy or charging power capacities are not necessary to accommodate imminent travel, can use those resources to provide grid services. Furthermore, because many grid services in many electrical jurisdictions are bought and sold in a relatively free and competitive market, vehicle owners could be compensated for such use through financial mechanisms that are, for the most part, already in place. Literally, you could rent out the use of your EV battery and/or power electronics to a utility or grid operator while your car is parked in your driveway.

From the perspective of electric vehicle operation and readiness for travel, grid services can be broken down into two classes; those that are at least in principle energy neutral over the timeframes of interest to vehicle owners, such as reactive power compensation and frequency regulation, and those that are energy consuming over such time periods, such as spinning reserves and peak support (Kempton, Tomić 2005a). Most examples in this later category can be conceptually tied to energy negative (i.e., energy consuming) services such as valley filling, but those will not be addressed here due primarily to the fact that with grid-wide communication systems, the market for consuming excess power will likely fill quickly. For a good overview of grid energy services, review Kempton and Tomić (Kempton, Tomić 2005a).

The resource potential that vehicles offer for these two types of services are not equal, even where the units in which they are traded are. For instance, spinning reserves and frequency regulation are both measured and billed in units of power capacity, made available for a length of time (e.g. MW-h, or kW-h). The two are similar in some ways, but with spinning reserves the risk that the ability of a specific vehicle to provide spinning reserves will be limited by available stored energy (kWh), rather than discharging power (kW), is higher than it is for frequency regulation. This is because of structural differences in the markets, in this case, the allowable length of a call. In this chapter, therefore, both the factors affecting system-wide stored energy, and those affecting available power will be explored.

It should be noted that the organization and structure of electrical stability and reliability markets are neither universal nor immutable, so current market configurations affect the analysis of potential service from vehicles presented here. Diverse market configurations exist throughout the United States and throughout the world, while in many jurisdictions (notably, in vertically integrated utilities) no open energy service markets exist at all. A good example of this variability is the Frequency Regulation market, which is also of particular interest as it is likely to be the highest valued market for GIVs (Kempton, Tomić 2005a). In some jurisdictions, a 1 kW capacity bid in the regulation market constitutes a commitment to deliver both 1 kW of increased load (Regulation Down, or Reg Down) and 1 kW of increased supply (Reg Up), on command. In other markets, quantities of Reg Up and Reg Down can be bid separately. Also of interest for EV or other battery energy storage participation, the frequency regulation market is being modified to the point of reinvention in many jurisdictions by the implementation of FERC order 755, discussed in section 1.4 (FERC 2011). For a summary of differences in several regulation markets, see Codani, Kempton and Levitt (Codani, Kempton, Levitt 2013).

The focus of this analysis will be the evaluation of the relative value or revenue generating potential of various configurations of vehicles, in various configurations of markets. For two reasons, I consider the most important and likely scenario to be that of vehicles plugged in at home. The first reason is, as has been mentioned in previous chapters, that home charging infrastructure is almost certainly going to be the first such infrastructure available to most EV drivers, and the location at which most time is spent parked. As we saw in Figure 1, for every hour that vehicles spent at their second most parked-at location ('work'), they spent about four hours parked at Home locations. The second is that, in locations other than home, the priority use of charging infrastructure should probably be supplying EVs with the energy they need to complete their upcoming travel, rather than as a mechanism of revenue for some individual. Despite this, the possibility of plugging in at work is very real, and likely to significantly increase the service potential of certain individual cars, so that scenario and the 'charging everywhere' scenario will also be evaluated.

9.2 Value of Frequency Regulation Service

Frequency Regulation to support grid stability is arguably, though is has dropped in value in the last few years, may remain the best suited market for quick-response energy systems. It is the highest valued capacity market for vehicles that can back-feed electricity (Kempton, Tomić 2005a). Spinning Reserves markets have historically cleared prices that are 10 – 50% those found in Frequency Regulation markets, so it may be less lucrative for vehicles owners. In the US, the implementation of FERC

Order 755, only partially implemented, is redefining the valuation of Frequency Regulation in such a way that the potential revenues for fast-responding resources such as batteries in cars may be dramatically increased (FERC 2011).

The following derivations of market service value are performed in the context of the Frequency Regulation Market, but should in principle apply to other capacity markets such as spinning reserves, or potential new markets such as power factor correction. The condition of energy availability limiting service will be examined in more detail in Section 9.5. A discussion of battery wear may be appropriate to fully evaluate the desirability of frequency regulation (De Los Ríos et al. 2010, Peterson, Apt & Whitacre 2010), but that is highly dependent on battery chemistry, charging rate, command signal, and thermal control, and in addition to changing with each new generation of vehicle traction batteries, is beyond the scope of this analysis. Where zero net energy is required for formulas to function it is so noted.

9.2.1 Time Needed for Charging

The amount of time that vehicles, which we assume are to be used primarily for transportation, can provide energy neutral grid service depends on two things; i) the amount of time they spend plugged in, and, ii) the amount of time needed to refill the batteries. The time needed to refill batteries depends on the rated power of the charger and on the amount of energy that has been removed from the battery since the last full charge, which in almost all cases will be the energy used for transportation. If E kWh are used to drive then those *E* kWh must be replaced. For a vehicle that has the capacity to charge at *P* kW, the time needed to charge will be *E/P* hours.

Fleet wide average utilization values were established in Chapter 5, where the average daily distance travelled by the vehicles in the study was found to be 32.6 miles, and this was found to have occurred, on average, on about 310 days during the year (refer to Figure 4). Using our model assumption 280 Wh/mile (section 2.4), this daily driving distance implies that vehicles will need to replace 9.1 kWh per day, or about 2.82 MWh per year. Charging from a 3.3 kW power source, this will take approximately 2.76 hours each driving day, or 855 hours in a year. The average amount of time a vehicle spends parked at its home parking location was established in Figure 1 as 70% of the year, or 6100 hours/year. Subtracting 855 hours from an average value of 70% of time at 'home', results in an average annual availability for grid services of 5245 hours in a year, or 60% of the time.

9.2.2 Value of Modulated Charging; Symmetrical Regulation Bid

For GIVs that are not capable of sending power back to the grid, the ability to provide regulation services is present only while the vehicle is able to absorb and stop absorbing power on command. For these cars that can only charge or cease charging, the amount of energy used for transportation or other services therefore defines the value potential of each vehicle, in a linear relationship, as described below.

Using the same variables as in section 9.2.1, if E kWh are used on each of the (typically) 310 driving days, then only E kWh of 'energy space' exist to be filled. For a vehicle with the capacity to charge at a rate (of power) P kW, the default charge rate in a symmetrical bid regulation market could be set to $P/2$ kW, and the offered capacity in both the Reg Up and the Reg Down markets would likewise be $P/2$ kW. At a symmetrical market price of c \$/kW-hour, this services would be worth $cP/2$ \$/hour. This service could be provided until the empty E kWh in the battery fill, which disregarding variations in state of charge caused by providing the service, would take $E/(P/2)$ hours each day.

The value that each car would provide to the grid would thus be the price c \$/kW-hr, multiplied by the bid capacity $P/2$ kW, multiplied by the duration of service $2E/P$ hours; this is cE \$/day. Note that this value is independent of the maximum charging rate P, containing only the price, and the daily energy consumption. On an annual basis with N driving days per year, this translates to

$$NcE \text{ \$/year} \qquad \text{Eq. 1}$$

Equation 1 shows that, for an EV that can only charge, not discharge, annual revenue potential in a symmetrical bid capacity market is independent of the maximum charging rate P. The caveat to this being that on days when the vehicle cannot fully recharge in time for its next trip at an average power of $P/2$ kW, providing grid service would be abandoned in favor of successfully completing upcoming travel.

As the preceding derivation has shown, frequency regulation revenues for charge-only cars in symmetrical markets are linearly proportional to the daily energy consumption, or by extension, to the annual energy consumption if full charging power is rarely required to prepare for the next trip. Extending the example in section 9.2.1; if the typical small vehicle consumes 9.1 kWh per day, and is used 310 days per year, then NcE \$/year, in a Frequency Regulation markets with an average price of \$40 / MW-h, is [310 days/year * 0.04 \$/kW-h * 9.1 kWh/day] = \$113/year.

9.2.3 Value of Modulated Charging; Asymmetrical Regulation Bid

More flexibility to optimize charging behavior for market participation is available in asymmetrical regulation markets, where the quantities of service offered to Reg Up and Reg Down may be unequal. Once again assume that vehicles are plugged in a total of T hours per day. With E kWh of energy consumed during the preceding driving, the average charging power needed to charge the battery while spending as much time as possible providing grid services will therefore be E/T kW.

Assuming a maximum charging rate P, and further assuming that $P>E/T$ (i.e., that the vehicle has more than enough time to recharge before the next trip), the vehicle can in principle participate in both the Reg Up and Reg Down markets. With different amounts committed to the Up and Down markets, an energy neutral Regulation signal will produce a non-energy neutral response. Accounting for this, it is possible to solve for the charge set point S (which in most cases will not be equal to E/T), by including a dispatch to capacity ratio (or regulation signal capacity factor) f, which describes how much energy is called for in a given hour, in each market, for a given capacity commitment.

With a set point S as the default charge rate, S kW can be bid into the Reg Up market, and (P-S) kW can be bid into the Reg Down market. The average charge rate, E/T, must equal the set point S, less the energy transferred out due to Reg Up participation; fS, plus the extra charging due to Reg Down participation; $f(P-S)$. The equation $E/T = S + f(P-S) - fS$, can be solved for the charge rate set point S;

$$S = (E/T - fP)/(1-2f) \qquad \text{Eq. 2.}$$

Note that in Equation 2, as f approaches 0.5 (for both the up and down markets), the command approaches a square wave spending half of the time at 100% Reg Up dispatch, charging at a rate of 0 (i.e. not charging at all), and half of the time at 100% Reg Down dispatch, charging at full power P. At that point, the set point S becomes irrelevant, since the square wave will look the same regardless of what point within its range is considered 'neutral'. As f approaches zero (at which point none of the contracted regulation is ever called), S approaches E/T. In other words, if no regulation is called, the charging set point is simply that charging rate necessary to recharge the battery in time for the next trip.

In a vehicle that cannot back-feed power to the grid the set point S is limited to being greater than or equal to zero, which is to say $0 \leq S = (E/T - fP)/(1-2f)$. Therefore, because f is limited $f \leq 0.5$, we know that $E/T \geq fP$, which rearranged come to the very intuitive $E \geq fPT$, stating that the amount of energy E that will make it into the battery in time T will be greater than or equal to fP, which is the average charging power when S is set to zero and the entire charging capacity P is offered to the Reg Down market. Similarly, $T \leq E/fP$, which indicates that the time it takes to fill the battery will be less than or equal to the time it would take using only Reg Down charging.

Equation 2 tells us that the optimal Reg Up bid in an asymmetrical market is $(E/T - fP)/(1-2f)$ kW, while the Reg Down bid should be $(P - fP - E/T)/(1-2f)$ kW. At an average Reg Up market price of c_u \$/kW-h, and Reg Down price of c_d \$/kW-h this services would be worth

$$(1/(1-2f)) * (c_u(E/T - fP) + c_d(P(1-f) - E/T) \text{ \$/h.} \qquad \text{Eq. 3}$$

Since this service will be provided for T hours per day before the battery is full, the value per day becomes $(1/(1-2f)) * (c_u(E - fPT) + c_d(PT(1-f) - E)$ \$/day. Making the assumption that the value of Reg Up will exceed that of Reg Down by a factor of 2 (which has historically been a reasonable approximation in the CAISO), and defining the sum of these two values c_u and c_d as c to make them comparable to Equation 1, produces the simplified daily revenue formula

$$c/(3-6f) * (2(E-fPT)+(PT(1-f)-E)) \text{ \$/day} \qquad \text{Eq. 4.}$$

Equation 4 (including the factor of 2 assumption about the price of Reg Up vs. the price of Reg Down) can be used as a basis of comparison with the symmetrical market scenario presented in the previous section. Revenue potential in these two market structures for a small EV with modulated charging is of interest. To compare revenue potentials, however, an estimate of the dispatch to contract ratio f is needed. Kempton & Tomic (Kempton, Tomić 2005a) perform an analysis of CAISO regulation signals and find that the dispatch to capacity ratio is just 8%. Fertig & Apt (Fertig, Apt 2011), find that average dispatch in the ERCOT frequency regulation market is 20% of capacity (ERCOT 2010). A third analysis performed by the author on CAISO date provided by NRG Energy Inc. as part of a report relating to V2G in California (unpublished) found values for f between 0.07 and 0.1. For the following calculations a value of $f = 0.1$ will be used, but it should be noted that the degree to which this is representative of any given electrical systems is unknown. Furthermore, the preferential dispatch, fast-response regulation markets being developed under FERC Order 755 is likely to make any values found prior to their implementation inapplicable to forward-looking analyses (FERC 2011).

Since our example vehicle spends 70% of hours on a plug, it spends 30% of the year (2628 hours) away from the plug throughout the year, or 8.5 hours on each of 310 days of use, thus 15.5 hours are spent on plug per driving day. It consumes 9.1 kWh on each of those 310 days, and has 3.3 kW charging capacity. Using a price ratio c_u : c_d of 2:1, and a regulation dispatch ratio *f* of 0.1, Equation 4 tells us its annual revenues would be $232. This compares favorably with the $113 per year revenue found in the previous symmetrical bid market scenario.

There are however two variables about which a great deal of uncertainty persists; the regulation signal capacity factor *f*, and the ratio of Reg Up to Reg Down market price c_u : c_d. Because of this uncertainty, a more complete description of the revenue potential of a charge rate-modulating vehicle is presented below in Figure 35.

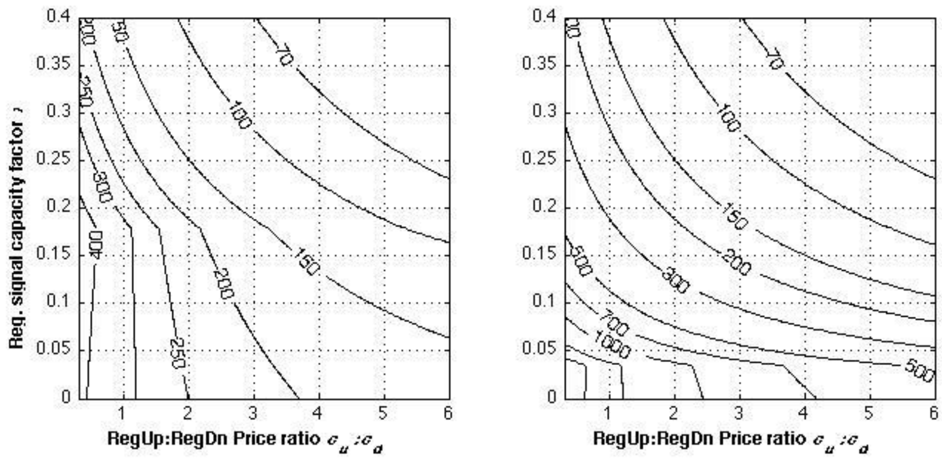

Figure 35: Revenue potential in an asymmetrical bid Regulation market, assuming \$40/MW-hr combined up/down price, for 3.3 kW charging (left) and 17 kW charging (right).

Figure 35 shows the annual revenue potential for a (non-V2G) GIV operating in an asymmetrical bid Frequency Regulation market, consuming 9.1 kWh of electricity on each of 310 driving days during the year, and recharging at a maximum rate of 3.3 kW (left plot) or 17 kW (right plot). The market price for Reg Up and Reg Down are assumed to sum to \$40 per MW-hr. To adjust the results to a different average market price, a simple ratio can be applied to the results.[24]

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[24] As previously stated, this calculation neglects diurnal variations in the market price of regulation service, changes in instantaneous state of charge due to the act of

In Figure 35 the ratio of prices for Reg Up and Reg Down ($c_u : c_d$) is presented on the x-axis of each plot. For example, if the price of Reg Up is twice that of Reg Down (2 on the x-axis), and the capacity factor *f* is 10% (0.1 on the y-axis) the annual revenues on a 3.3 kW plug (left plot) may be seen to be a little bit closer to $250 than to $200, which agrees with the $232 per year found above.

The 'kink' that appears in both plots, at about the $f = 0.18$ level on the left plot and at about the $f = 0.04$ level on the right plot, corresponds to the point above which the default charge rate *S* falls to zero (0 kW). Conditions at this point will be discussed in the following section (section 9.2.4). Below the 'kink', both Reg Up and Reg Down services are provided throughout the *T* hours when the vehicle is plugged in, and revenue potential can be seen to increases with greater Reg Down price (moving further to the left in the plot). Of interest is that the effect of the regulation capacity factor *f* on potential revenues is variable. When Reg Up is more valuable than Reg Down ($c_u : c_d > 1$), a greater capacity factor *f* results in less revenue. When Reg Up is worth less than Reg Down ($c_u : c_d < 1$, which seems an unlikely scenario but was included for completeness), then higher dispatch *f* results in decreased revenue potential.

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providing regulation service which are assumed to be small, as well as limitations on a vehicle's ability to provide grid service imposed by higher and lower mileage days.

Of note in Figure 35 is the fact that more unequal values for Reg Up and Reg Down in an asymmetrical market are bad for vehicle revenues. This makes sense given the simplification used for this analysis that the sum of the two values is a constant, because as long as $E/T<P/2$ the vehicle will supply more Reg Down than Reg Up. For values of P less than twice E/T, more Reg Up will be provided, so greater price disparity in favor of the price of Reg Up will increase revenues. Returning to the previous example, where E is 9.1 kWh and T is 15.5 hours, that point occurs where maximum charting power is less than 2 * 9.1 kWh / 15.5 h = 1.2 kW. This reveals that only for very low charging powers (or for cars that use lots of power each day, or cars that spend very little time on a plug), higher relative Reg Up prices would increase revenues.

This relationship is explored further in Figure 36, where the annual potential revenue is mapped against the regulation capacity factor f (as before) and the 'normalized charging power' defined as $P/(E/T)$. Normalized charging power is thus the ratio of the maximum charging rate to the charging rate needed to recharge on the average day. Isographic lines representing conditions of constant annual revenue are plotted against these variables, assuming combined regulation market price $c_u + c_d =$ \$40/MW-hr, and the two prices are equal (left plot), or differ in price by a factor of 3 (right plot).

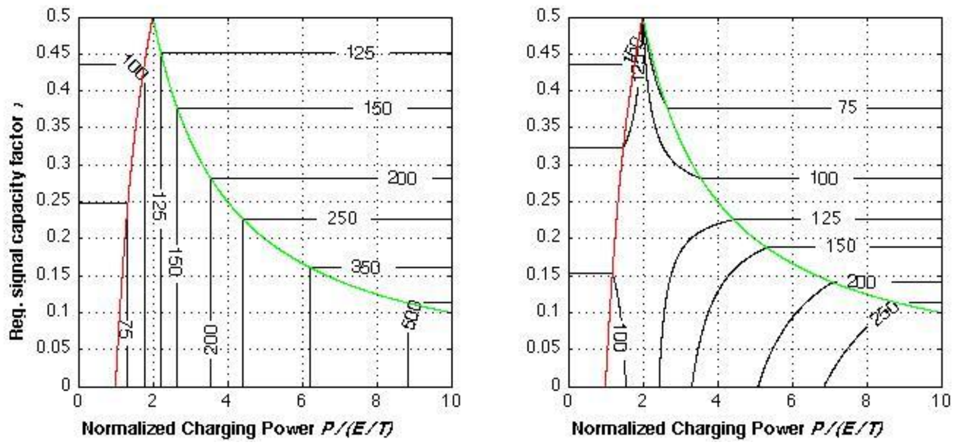


Figure 36: Revenue potential from charging 9.1 kWh on each of 310 driving days in an asymmetrical Regulation market where Reg Up and Reg Down are i) each priced at \$20/MW-hr (left plot), and ii) are priced at \$30 and \$10 / MW-hr respectively (right plot).

There are three 'zones' evident in Figure 36. Above and to the right of the green line, vehicles operate only in the Reg Down market, corresponding to the area above the 'kink' in Figure 35, and charging is complete before T hours have elapsed. (Bidding into the Reg Up market would require a higher default charge rate, and would thus charge even faster). In Figure 35, different values of charging power P were used in the left and right plots, the kink appeared in different locations. Similarly, the values of f which only permit participation in Reg Down is seen to decrease with increasing charging power. I.e., the green line in Figure 36 slopes down with respect to as *P/(E/T)*. Between the green and red lines vehicles participate in both Up and Down markets for the full span of T, though at the green line participation is all Reg Down, and at the red line participation is all Reg Up. To the left of the red line, P is so low that the Reg Up charging rate fP kW will not supply E kWh within T hours. By charging at P for at least part of the time, rather than fP, part of the area to the left of the red line would be reclaimed, but that scenario was not reflected in equation 5.

The most interesting finding in Figure 36 is that for unevenly priced asymmetrical markets (right plot), in certain conditions down-rating the charger can increase regulation revenue. This can be seen in the right plot of Figure 36 (where $c_u : c_d = 3$), between the red and green lines and above $f = 0.25$ where the slopes of the lines of constant revenue are negative. The negative slopes indicate that by decreasing the effective charging power P (and thus the effective normalized charging power $P/(E/T)$), more money may be earned. This can be explained as being able to sell slightly more of the more valuable Reg Down by supplying significantly less Reg Up. This only applies to values of f higher than those observed in the cited studies for ERCOT and CAISO, but may be relevant in the new fast-response markets emerging under FERC order 755, if qualifying resources are preferentially dispatched.

9.2.4 Regulation Down Market Participation Only

In certain conditions, it is preferable not to offer any capacity to Reg Up service. Above the 'kink' in Figure 35 and to the right of the green line in Figure 36, the default charge rate S is 0 kW. In these conditions, therefore, filling the battery is accomplished exclusively by providing P kW of Reg Down service, charging at an average power of fP kW. This service can be provided until the battery is full, which with E kWh of 'empty' space to fill happens in E/fP hours. At a Reg Down price of c_d \$/kW-hr, each vehicle therefore provides $c_d * P * E/fP$ worth of service on each driving day:

$$c_d E/f \text{ \$/day} \qquad \text{Eq. 5}$$

As was the case in section 9.2.2, the revenue potential for offering only Reg Down, described by equation 5, is independent of charging power capacity P. Corresponding to this finding, above that 'kinks' in Figure 35 there are no differences in revenue for higher power charging (left vs. right plots in Figure 35), and the lines of constant revenue potential in Figure 36 are perfectly horizontal, indicating no change in revenue as the normalized charging power $P/(E/T)$ changes.

In terms of regulatory compliance or rules for market participation, if the value of the default set point S discussed in the previous section is sufficiently small (i.e., vehicles operating at a point to the left of, but near to, the green line in Figure 36), then even a large fleet of vehicles may fail to provide enough capacity to qualify for participation in Regulation Up markets. In such a case, vehicles may be limited to participation only in Reg Down markets even if operating at points slightly below the 'kink'.

9.2.5 Value of Back-feeding (Vehicle-to-Grid)

The value proposition associated with backfeeding electricity for Frequency Regulation (or for any other capacity based grid service) has been shown to depend on a high power grid connection (Kempton, Tomić 2005a). An analytical solution for the value of V2G service can be simply derived using the variables introduced in the preceding sections, assuming that the maximum rate of charge P kW is also the maximum rate of V2G discharge into the grid. (It should be noted that in some (Nissan Motors 2012, Kempton et al. 2008), but not all (Mitsubishi 2012)) implementation of backfeeding electricity this is the case). In a capacity market with a value of c \$/kW/hour, the value of selling a power capacity of $\pm P$ kW is cP \$/hour, consistent with previous variable definitions. For a vehicle that spends T hours per day on plug and E/P hours of that time charging, the revenue potential is thus $(T - E/P) * P * c$ \$/day, or:

$$c(PT - E) \text{ \$/day} \qquad \text{Eq. 6}$$

An alternative strategy, possible if the schedule of upcoming travel is know, might be to set the default rate of charge to E/T kW which will, ignoring variations in SoC that result from providing the service, mean that the battery will arrive at 100% SoC just when the next trip is scheduled. (This scheme corresponds to what was described in

Chapter 8 as Charging Algorithms 7 & 8 'Charge at a Constant Rate'). In a symmetrical bid market the offered capacity in each of up and down regulation would then be $\pm(P - E/T)$ kW. Providing this service at an average (symmetrical) market price of c \$/kW/hour would earn a revenue of $c(P - E/T)$ \$/hour. Since this would take place for T hours/day, daily revenues would likewise be $c(PT - E)$ \$, the same value found in equation 6.

The comparison of these two strategies does not take into account the possibility that as the battery fills, the ability to provide Regulation Down will be limited by the reduced amount of 'energy space' remaining. These derivations indicate that since no potential revenue is lost by sequentially providing regulation and then charging, as long as the start time of the next trip is known, that is a better strategy because it retains available 'energy space' (unfilled battery). In contrast, if the subsequent departure time is not known, the second approach may be preferable, as it will leave a fuller battery at any given point while the vehicle is plugged in, though revenue generation may be limited as the battery approaches 100% SoC, if calls for Reg Down (charging) cannot be accommodated.

The example EVs used elsewhere in this chapter has a charging power P of 3.3 kW and a daily energy consumption of 9.1 kWh. Doing this 310 days during a year, 2.82 MWh will be needed, which when charging from a 3.3 kW power source will take 830 hours in the year. Subtracting 830 hours from an average value of 70% of time on a 'home' plug (Figure 1), or 6100 hours/year on plug, results in an average annual availability for grid services of 5270 hours. For such a V2G capable vehicle the total annual volume of frequency regulation service would be 5270 hours at 3.3 kW, or 17.4 MW-hr each year. At the previously used average price of \$40 per MW-h, the value of frequency regulation provided by the vehicle described above would be \$696 per year. This compares favorably with any of the charge-modulating scenarios presented in the previous sections, and according to equation 6 will increase with charging power *P* at a rate slightly better than linear. (This theoretical result can be compared to observed values presented in section 9.5).

Table 11: Summary table of annual revenue potential for GIVs. All values assume 310 driving days per year and 6100 hours/year at a GIV-compatible plug. Market assumptions are \$40/MW-h capacity market price (\$13 Reg Down, \$27 Reg Up), with a signal capacity factor of 0.1. The four columns represent vehicles with different daily ranges and power capacities; i) 10 miles & 3.3 kW, ii) 10 miles & 16 kW, iii) 50 miles & 3.3 kW, iv) 50 miles & 16 kWh.

Daily Range (miles)	10	10	50	50
Charging Power (kW)	3.3	16	3.3	16
Symmetric Capacity Market				
NcE	\$35	\$35	\$174	\$174
Asymmetrical Capacity Market				
$c/(3-6f) * (2(E-fPT)+(PT(1-f)-E))$	\$182	\$825	\$239	\$882
Regulation Down only				
c_dE/f	\$113	\$113	\$564	\$564
Full V2G with back-feeding				
$c(PT - E)$	\$770	\$3869	\$632	\$3730

Table 11 shows the wide range of annual revenue potentials from different GIV scenarios. These values vary with i) market conditions, totally independent of the vehicle other than via its location, ii) with vehicle capacities, determined with the purchase decision or the vehicle design, and iii) with the use pattern of the vehicle, prescribed by the owner and her transportation needs. It must be emphasized that the highest values are only available to vehicles capable of back-feeding electricity, or V2G, which is a property intrinsic to the vehicle design (class ii)).

9.3 Observational Valuation of V2G; Time, and Idle Time at a Plug

The energy storage potential in EVs' batteries is of no use to grid operations if 'the grid' has no access to that energy. Access is contingent on three things; i) the vehicle must be plugged in (which means it must be at a location with an available EVSE and it must actually be plugged into that EVSE), ii) the vehicle must be able to communicate with a grid-serving entity (which I will assume is always the case when i) is met), and iii) since the first and most important role of an EV is to provide transportation services to the owner, it must not be using all of it's charging capacity to prepare for an upcoming trip. In this section, the V2G potential of a fleet of plug-in vehicles will be quantifiied using the Commute Atlanta data, by applying the travel model to determine requirements i) and iii) are met.

9.3.1 Time Spent at an Available EVSE (*T*)

The question of how much time vehicles spend parked at various locations has been examined in section 4.3 as a general characterization of the dataset, and in the context of charging and providing transportation services in Chapter 6. The same parameter, which was described by the variable T in section 9.2, is revisited here as a starting point of the investigation into V2G potential. The results of the analysis assessing the amount of time vehicle are plugged in at home and at work throughout the year is presented in Figure 37. For this analysis of the data, the graph has been modified from the version presented in Chapter 4 by counting Home and Work locations together, rather than separately, for the characterization of the second infrastructure build-out scenario.

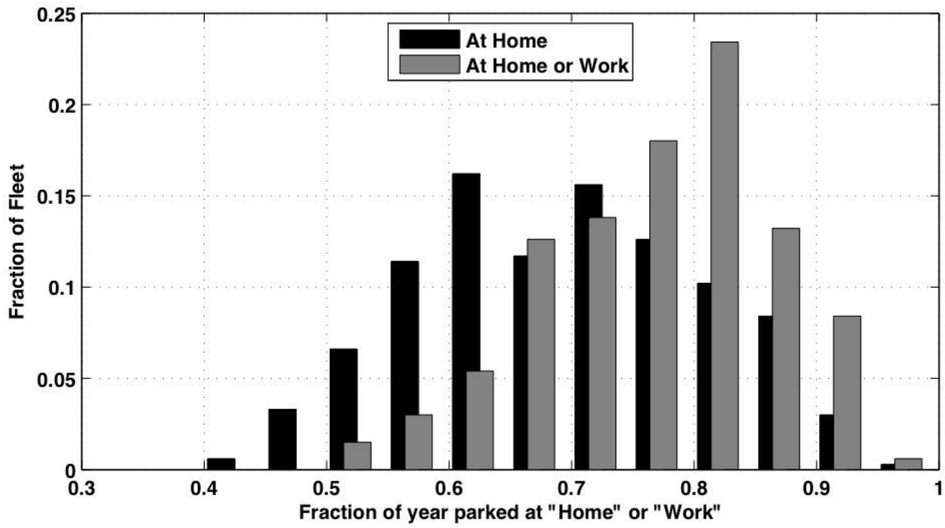


Figure 37: Distributions of time spent by the fleet of vehicles at "Home" locations (black bars), or at either "Home" or "Work" locations (grey bars), as a fraction of the year (x-axis).

In Figure 37, the black bars show the distribution among the fleet of the fraction of time spent parked at home. This is the same information shown in Figure 1, and it indicates that 68% of the fleet spends between 55% and 80% of the year parked at Home. Note that, compared to Figure 1, the scale of the x-axis in Figure 37 has been expanded for clarity. When parking at work or any second most frequented location is assumed to also offer an opportunity to plug in (grey bars), the distribution of time at an EVSE inevitably increases. The tallest grey bar in Figure 37 indicates that about 24% of the sample spends between 80% and 85% of the time parked either at Home or Work locations, and 81% of the fleet spends between 65% and 90% parked at one of those two locations. Across the fleet, the mean amount of the year spent parked at Home is 70% (median = 70%, both corresponding to the value used for *T* in section 9.2), with a standard deviation of 12%, while the mean amount of time cumulatively spent at either Home or Work is 78% (median = 79%) with a standard deviation of 9%.

9.3.2 Inter-Hour Variation of Idle V2G Capacity (*T – (E/P)*)

In analyzing the ability of plug-in vehicles to provide grid services, the next step after assessing how much time vehicles spend at locations with plugs is the analysis of the fraction of time vehicles spend at those locations, where we assume they are plugged-in EVs, but not charging. Whenever travel services are not limited by charging rate, the spare power capacity of the plug can be applied to grid services. This state of being plugged in but not charging will be referred to as being ‘idle’, and the power or energy resource of idle cars will correspondingly be referred to as ‘idle capacity’. This state corresponds to the parameter described by the formula *T – (E/P)* used in section 9.2, though that analysis did not account for variability throughout the day.

Analysis in Chapter 8 examined the charging power of the fleet of vehicles as a function of the time of day, and used as an example a typical 2012 Nissan Leaf-like vehicle with 24 kWh of battery capable of charging from a 3.3 kW EVSE. That same vehicle, when plugged in to an EVSE but not charging, can in the context of V2G grid services analysis be thought of as being a potential resource for the grid (though, it should be noted, a stock Nissan Leaf does not have the ability to feed electricity back to the grid through SAE designed EVSE plugs). The fraction of the fleet of such vehicles in this idle state, based on the assumption that they will charge right away upon plugging in and will charge until full (Charging Algorithm 1), is shown for home only charging in Figure 38.

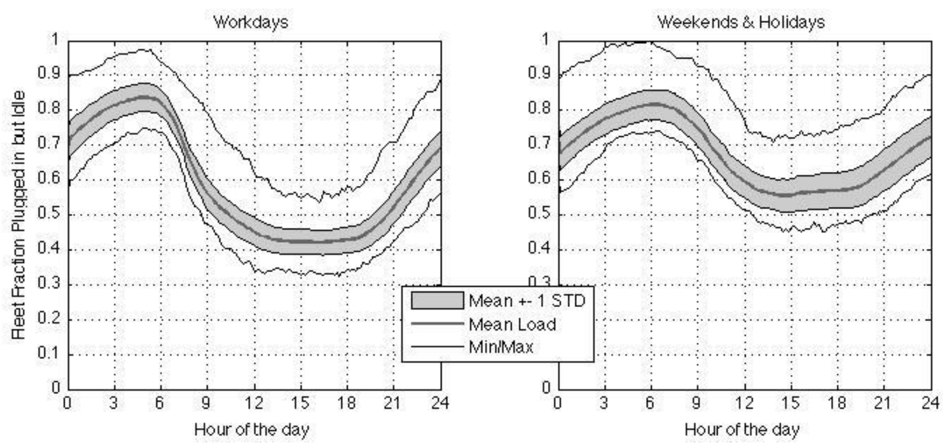


Figure 38: Fraction of the fleet of Nissan Leaf-like vehicles sitting plugged in at home that have finished charging. Mean, standard deviation, minimum and maximum fraction on workdays (left plot) and weekends and holidays (right plot) throughout the year

As with previous plots of fleet average inter-hour variations, the plot on the left in Figure 38 shows the fraction of the fleet that is idle for workdays, while the plot on the left shows it for weekends and holidays. The annual mean is indicated by a thick black line, the standard deviation about that mean and annual maximum and minimum values, based on the distribution among 251 workdays and 110 non-work days for each 10-minute time period, are indicated by a grey band about the mean, and thin black lines, respectively.

We know from the preliminary analyses described in section 4.3 that the population of vehicles at home rarely reaches 100%. From analysis in Chapter 8, we further know that many vehicles, particularly at low charging power such as this example 3.3 kW system, charge late into the night, so it is no surprise therefore to see that on weeknights (Figure 38, left plot) there is no point at which the entirety of the fleet is available and idle. What is particularly interesting from the perspective of grid operations or vehicle aggregation is that during the height of the workday, even though this example uses the most aggressive charging algorithm 'Charge Right Away' (refer to section 8.4) and the relatively low charging power of 3.3 kW, more than a third of the fleet is always on plug and idle at Home, and on average about 40 – 45% of the fleet is available throughout hours of lowest availability, 1200h to 1800h. On weekend and holidays, while the nighttime maximum available fraction is reduced (and delayed relative to that on weeknights, as was the peak fleet fraction parked at home), the daytime minimum availability is slightly higher, at about 55% on average, between about 1300h and 1900h.

When charging at work is added, based on the results of parking pattern analysis presented in Chapter 4, we anticipate an increase in mid-day and evening availability on workdays, and little change on weekends. Workday mid-day availability should increase because the roughly 40% of vehicles that are parked at work (Figure 2) are plugged in, and at least some of them will be idle. Workday evening availability should increase because some vehicles, due to being plugged in at work, have less charging to do when they get home and so contribute to the idle capacity earlier in the evening. The results of this analysis, again for a vehicle with a 24 kWh battery capable of charging at 3.3 kW, plugging in at home and at work, and charging right away at full power upon plugging in, is shown in Figure 39.

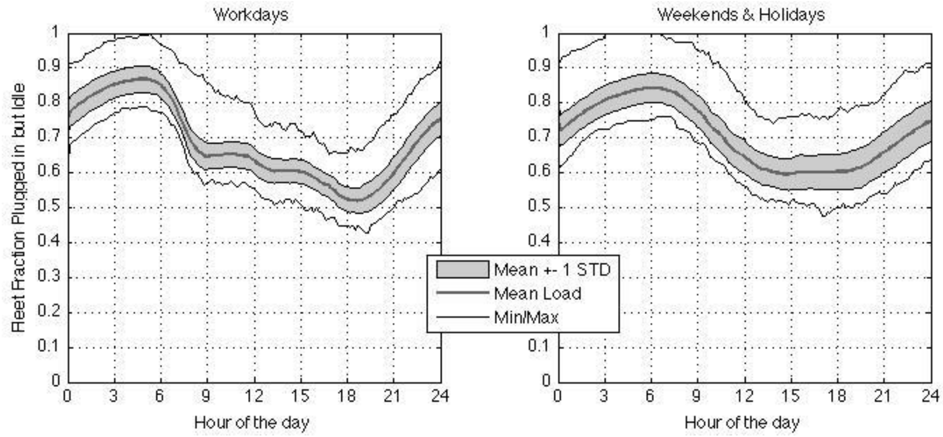


Figure 39: Fraction of a fleet of Nissan Leaf-like vehicles at idle, on plug but not charging, when EVSEs are available at home and work locations.

As anticipated, the addition of plugs at Work causes plug-in vehicles to be idle on their plugs still more of the time, meaning that a larger portion of the fleet is idle during working hours. The lowest idle fractions in this scenario occur on workdays when vehicles first get home around 1800h, because all commuting vehicles will need to charge at least briefly. Less evening charging is required however, so by midnight, on average 75% of the fleet is idle, compared to about 70% when no charging at work is available (Figure 38). Very small gains in vehicle availability are seen on the weekend (right plots of Figure 39 vs. right plot of Figure 38), which is consistent with the definition of workdays, and with vehicle parking location findings discussed in Chapter 4.

For reasons discussed previously, it seems unlikely that public charging infrastructure will frequently be used for grid services, however the ‘Charging Everywhere’ scenario is included here for completeness. The corresponding plot for vehicles with a 24 kWh battery and 3.3 kW charging capability of fleet idle state, when charging is available everywhere in shown in Figure 40.

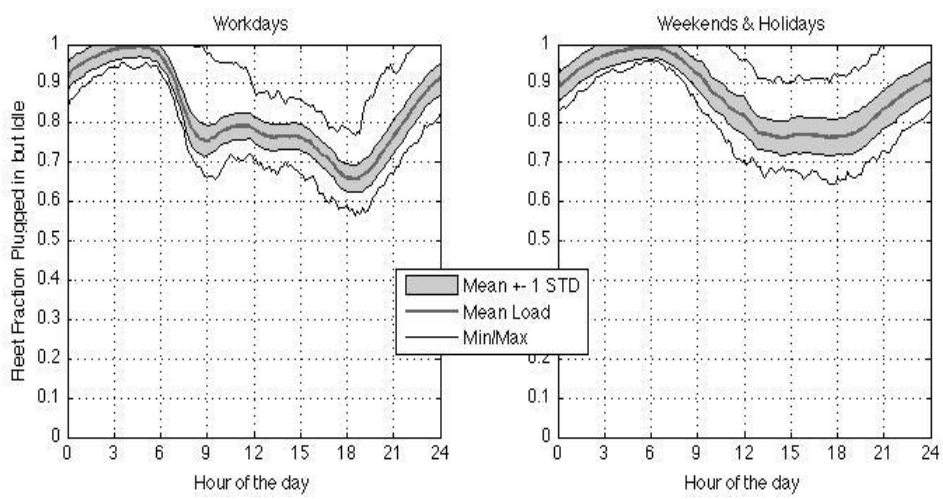


Figure 40: Fraction of a fleet of Nissan Leaf-like vehicles at idle, on plug but not charging, when EVSEs are available everywhere vehicles park for more than 30 minutes.

Figure 40 shows the fraction of vehicles on a plug but at idle when charging is available everywhere any vehicle parks for more than 30 minutes. This fraction is consistently very high, with dips during working days corresponding to the morning and evening commutes, and generally lower vehicle availability during the day both on working days and on weekends and holidays.

9.3.3 Vehicle Design Effects on Idle Time on Plug (*T – (E/P)*)

Of the variables under investigation throughout this research, two are intrinsic to the design of vehicles. The single-charge range, introduced in Chapter 5, is a function of the size of the battery and vehicle efficiency. The recharging rate or power *P*, introduced in Chapter 6, is a function of the capacity of the power electronics available for charging (and implicitly for this analysis; discharging back to the grid), though it may also be limited by charging infrastructure external to the vehicle. In the context of an investigation into V2G potential, the parameters of interest to vehicle design are correspondingly battery size and charging power. As in the analyses presented in previous chapters, it is also informative to compare the effects of changes to these two aspects of vehicle design to changes in the availability of charging stations.

Here, the same variables of battery size and maximum charging power are evaluated with respect to their influence on the potential to provide grid services. Using the variable definitions from section 9.2, this section evaluates the parameter T - E/P, which is the amount of time vehicles are plugged in and online but not charging, described as idle. When looking at the average fraction of the year during which service can be provided, inter-hour variability may be neglected. Because the various charging algorithms predominantly only adjust when batteries are charging (and thus when they are idle), no changes to the annual average online power of plugged-in vehicles would obtain from changing charging algorithm, so charging algorithm effects are not assessed. The exceptions to this statement are those algorithms that adjust the charging rate, these are Algorithm 3 “Half Rate During the Day”, which reduces idle time both during the day and the night, and the two “Charge at a Constant Rate” algorithms, 7 and 8 (discussed in more detail in section 8.4), which do not register any idle time on plug at all, since the entire span of time spent parked is used to charge, albeit slowly.

In section 9.3.2 the fraction of the fleet that would be idle and available was evaluated through time for a typical EV, here the time averaged availability is presented as a function of the vehicle design parameters. In Figure 41 the same range of vehicle characteristics examined in previous analyses is evaluated in terms of the fraction of time spend plugged in but not charging, for vehicles that plug in at home only. The iso-graphic lines in Figure 41 represent lines of equal time fraction $T - E/P$, averaged for the year.

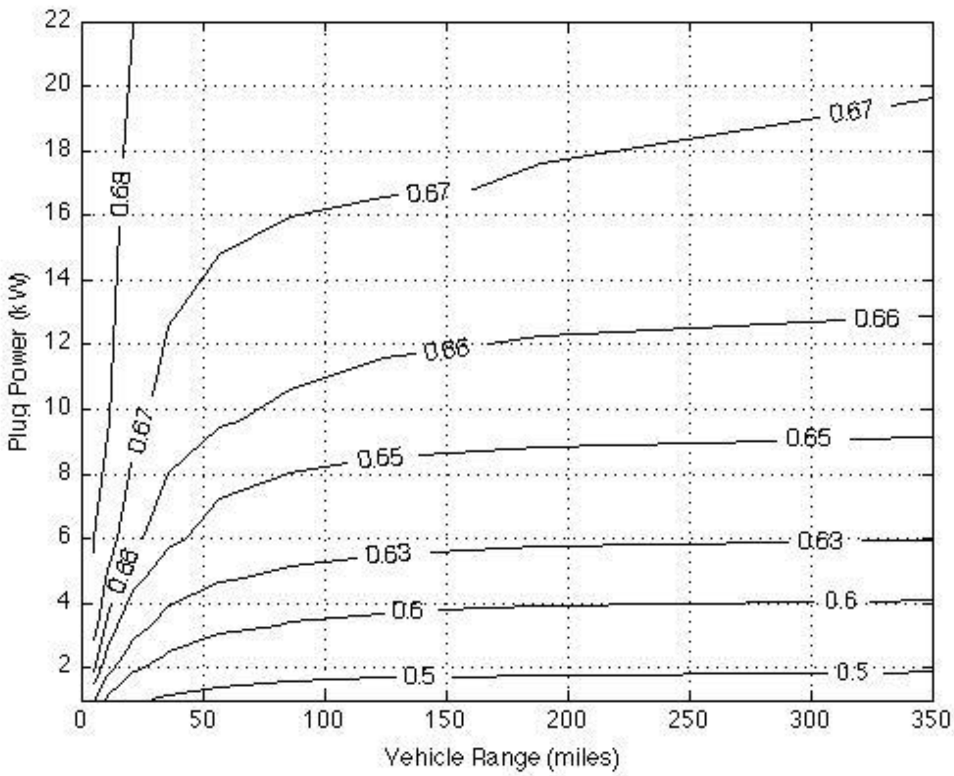


Figure 41: Fraction of the year vehicles could be providing V2G services if charging only at Home.

Figure 41 shows clearly that, as intuition would suggest, having a higher power charger at home has a dramatic effect on potential time providing V2G services. While long-range vehicles charging at 2 kW (bottom right of Figure 41) are able to provide V2G services just a little more than 50% of the time (4300 hours per year), increasing that to 6 kW bumps that up to just over 63% of the time (5400 hours per year). In sum, if you can recharge faster, more of your limited time at the plug is left over for V2G.

As with the vehicle substitutability and the grid loading analyses, the rate of improvement in the parameter falls off as plug sizes exceed 6 kW; note the unequal value separation of iso-graphic lines. The highest values in the range presented are less than 68% of the time (5800 hours per year), for vehicles with high-power plugs and very small batteries.

What may seem counterintuitive in Figure 41 is the fact that vehicles with smaller batteries have more idle time on plug. This can be explained simply by the fact all vehicles are assumed to spend the same spans of time plugged in at home (i.e., no adjustment is made for vehicles that might be left at home because of a foreseen inability to complete a given trip or day’s driving). Thus, for a given charging power, a smaller battery will fill faster. If such an adjustment was made, the amount of time lower-range vehicles would sit idle at a plug would increase even more, as the time they would otherwise be attempting trips that they cannot complete, and the time needed to charge up afterwards, would be added to the time available for V2G service.

By adding EVSEs at work, intuition and the evidence for a Nissan Leaf-like vehicle seen in comparing Figure 39 to Figure 38 would suggest that more idle time would result. The modeled results of the home and work charging scenario, again using charging Algorithm 1 “Charge Right Away”, are presented below in Figure 42.

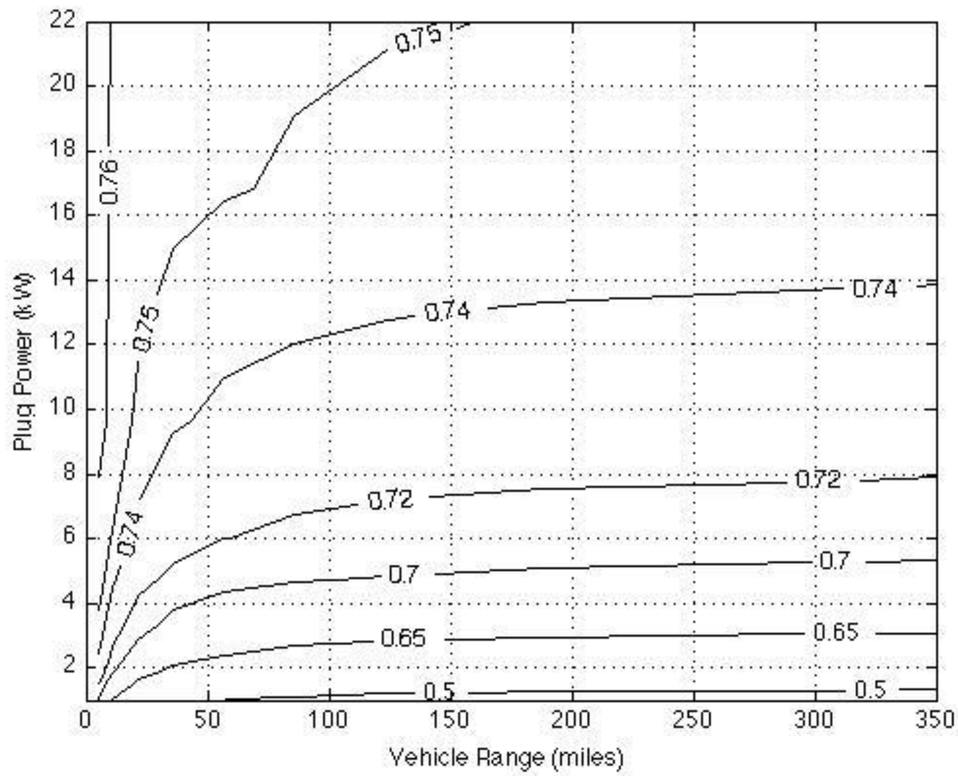


Figure 42: Fraction of the year vehicles could be providing V2G services if charging from Home and Work charging locations.

As anticipated, Figure 42 shows that when charging is available both at work and at home parking locations, the amount of time which vehicles could dedicate to providing grid support services is significantly increased. Where with charging at home only (Figure 41), a large-battery vehicle with a 6 kW charger could provide about 5400 hours per year of energy neutral grid services, with work charging added the same vehicle could provide about 6100 hours per year, a relative increase of 13%.

If the value of grid services is constant throughout the day, this would correspond to an increase in revenue for vehicle owners of a corresponding 13%. As before, both faster charging and smaller batteries increase the fraction of time vehicles would sit idle on a plug.

For completeness it is possible to evaluate the same vehicle design parameters in the context of totally ubiquitous charging infrastructure. Figure 43 shows the results of the 'plugs everywhere' analysis, wherein vehicles have the opportunity to plug in and charge everywhere they park for more than 30 minutes, and those vehicles provide grid services when they do not need to charge.

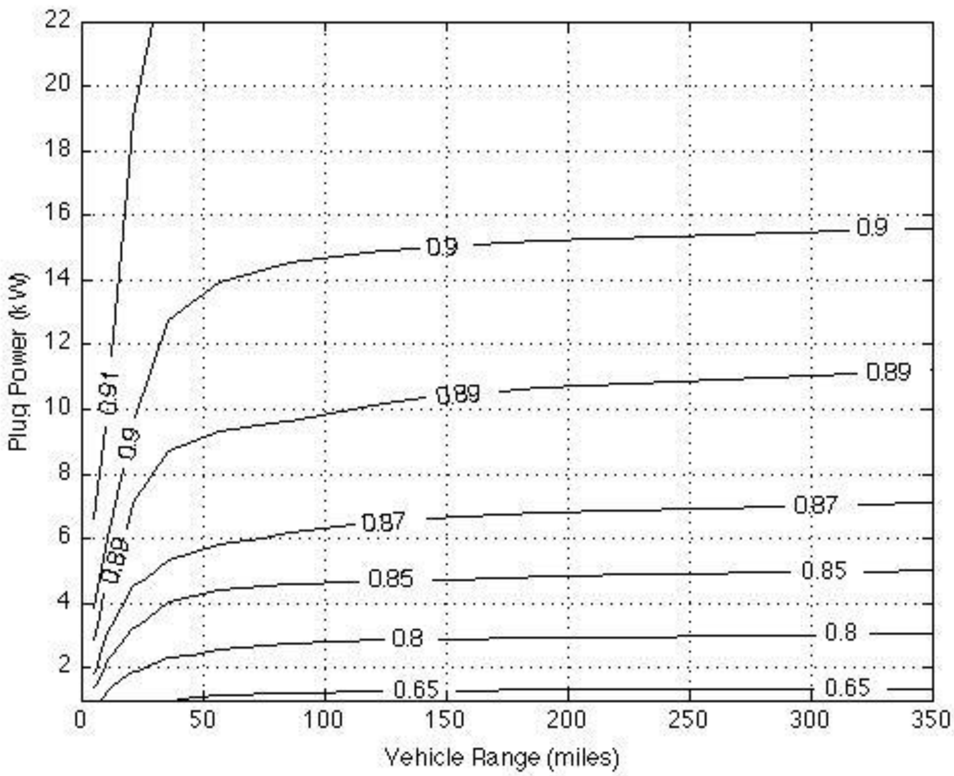


Figure 43: Fraction of the year vehicles could be providing V2G services if service is provided from all parking locations.

Compared to Figure 41 for home only charging, and Figure 42 for home and work charging, Figure 43 shows that dramatic increases in the amount of time cars spend on plugs but not charging would result from charging infrastructure existing at every parking space. Even the longer range, slow charging (2 kW) vehicles would spend two thirds of their time available to provide grid services, and that fraction increases both with smaller batteries and with faster charging (as before). Most plausible vehicle configurations (discounting vehicles with very large batteries and very low charging rates) would spend more than 80% of the year (7000 hours per year) as idle capacity, in principle capable of providing grid services.

9.4 GIV Service Potential of non-V2G Vehicles

In section 9.3, the service potential of GIVs was evaluated in terms of the amount of time they would spend plugged in, and time spent plugged in but not charging. Those parameters are only a partial description of the ability of any given configuration of vehicle to provide grid services as part of a distributed storage resource. In this section, a more refined parameter of 'Service Potential' will be explored for vehicles that cannot feed electrical energy back to the grid, i.e., non-V2G GIVs. (The service potential of V2G capable vehicles will be discussed in section 9.5). Service potential is a function of both the time available to provide service, and the amount of service that could be provide in a given time, either a measure of energy space availability, or power capacity, depending on the market being served.

9.4.1 Modulated Charging for Energy Neutral Services

For GIVs that do not have the ability to feed electricity back to the grid, the amount of grid service a vehicle can provide is primarily a function of the amount of 'empty space' that develops in the battery through time as a result of driving. This parameter corresponds to the variable *E* in section 9.2, where the reasons for this relationship were shown mathematically. In this section, the average amount of empty space in batteries connected to the grid is assessed based on the Commute Atlanta dataset.

The annual, fleet-wide ‘bulk’ property of energy space is simply a function of the annual distance driven (as discussed in section 9.2), and is equal to the theoretical maximum amount of grid service a vehicle could provide. The distribution of annual distance traveled (normalized across the fleet by the amount of time they were in the study) is shown below in the left plot of Figure 44. In the right plot of Figure 44, the corresponding distribution of annual potential service provision *E*, is presented, defined by annual energy consumption.

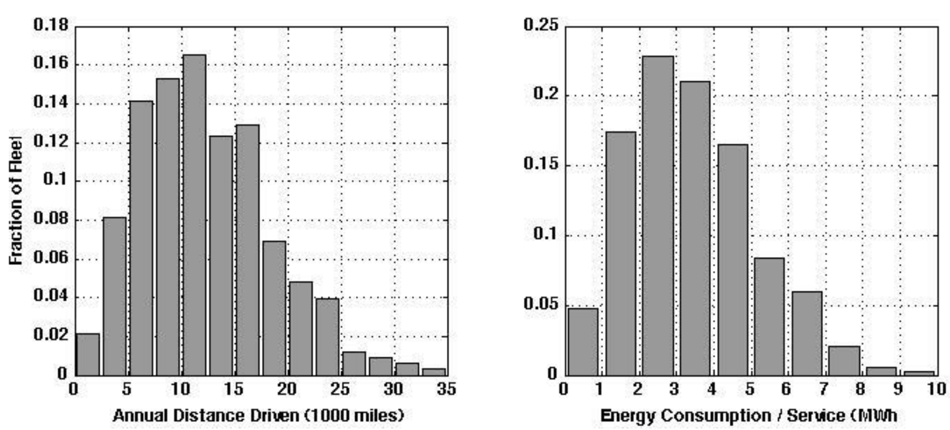


Figure 44: Distribution of Annual Distance Driven (left plot) and Annual Energy Consumption in MWh (right plot), which is equal to the theoretical limit of charge-modulated grid service provision.

The left and right pots of Figure 44 show distributions of linearly related data. The disaggregated data used to make the two distributions, miles driven per year and energy consumed per year, are related in this research by the assumed universal vehicle energy efficiency of 280 Wh per mile driven (refer to section 2.4). The distributions appear slightly different because the individual values are separated into different bins in the two plots, so that each has bin edges at round numbers of the units miles/year and MWh/year in the left and right plots, respectively. The fleet-wide average annual driving distance is 12,300 miles while the median is 11,500 miles. These correspond to 3.44 and 3.20 MWh of energy consumed per car each year, or grid service provided per car each year, respectively. The standard deviation is relatively large, at 6100 miles, or 1.7 MWh of grid service, due to the long-tailed nature of the annual total vehicle travel distributions.

It must be reiterated that while energy space can be used to provide grid services through charging rate modulation, there will be occasions when charging at full power to prepare for upcoming trips will take precedence, so these values are theoretical maxima. The fraction of these grid services that would be limited by charging for upcoming travel depends on both charging power and battery size, which also determine how many individual trips a limited range EV would attempt. Previous evaluations of the effects of charging power (section 6.5) however, suggest that the frequency of these occasions is very small once charging powers exceed about 6 kW.

More refined estimates of the actual capacity to provide grid services depend on specific driving patterns and charging algorithms, and are discussed below.

9.4.2 Potential for Modulated Charging based Services; Energy Space Online

Figure 44 shows the distribution of annual total energy consumption, and thus total refillable battery 'energy space' in a fleet of plug-in vehicles that completes all travel using grid electricity. More detailed analysis of the portion of this space to which grid service entities would have access at any given time, which will subsequently be referred to as 'Energy Space Online' (ESO), is determined by two factors: i) vehicles being away from plug locations and therefore by definition not 'online', and ii) the amount of energy storage being refilled by recharging, subject to the timing of a recharging algorithm. For grid services that require the absorption of 'excess' energy over timescales relevant to vehicle trip-making (such as overnight valley filling), the time of day at which ESO is available is an important consideration.

Assessing the financial value of Energy Space is at best ambiguous. To monetize the ESO resource requires not only a market that rewards the ability to absorb energy when there is a positive imbalance on the grid, but it also requires that the GIVs online have discretionary charging power capacity. To use a simple example; a grid seeking to address an oversupply of wind energy (wherein wind generation output approaches or exceeds system load), would require that the fleet of GIVs not only have ESO, but that the fleet can increase charging power, because charging power capacity already in use would count towards existing load.

Thus for grid services that rely on ESO in the batteries of non-V2G GIVs, the effective rate of charging while providing such services becomes very important. In that context, the effective charge rate will be some fraction of the plug capacity *P*. Depending on the nature of the market being addressed and the details of a specific sequence of travel and parking (refer to section 9.2), the average rate at which the battery fills may be only *fP*, (the capacity factor of the signal *f* times the plug nominal power *P*), or may be *P*/2, half the nominal charging power, or other values bounded by 0 and *P*. Because the market structures that determine this factor vary between electrical jurisdictions, average charging power has been left as a variable in the following analysis, taking the place of maximum charging power.

Figure 45 shows the amount of ESO per vehicle (averaged across the fleet) as a function of time, on workdays and weekends. As in previous analyses, two battery sizes have been used to represent the spectrum of vehicle ranges in GIVs; 16 kWh and 53 kWh. Because many vehicle configuration and charging infrastructure scenarios are of interest, many different configurations have been evaluated and are shown in Figure 45. As in Figure 24 in section 8.2 which showed grid load for a number of vehicle and infrastructure configurations, Figure 45 plots workday ESO on the left, weekend and holiday ESO on the right, and the three infrastructure scenarios in which vehicles can charge at 'Home Only', at 'Home and Work', and 'Everywhere', in three rows. In each of the 6 resulting plots, 12 vehicle design scenarios are displayed; 12 lines trace ESO through 24 hours of each day corresponding to vehicles with 16 and 53 kWh batteries, which charge at average rates of 1, 1.5, 2, 3.3, 6, and 9.6 kW when plugged in. These charging powers are lower than those used in previous analyses because, as discussed above, the availability of discretionary charging power (the ability to increase charging load) is a necessary condition of deriving value from an ESO resource.

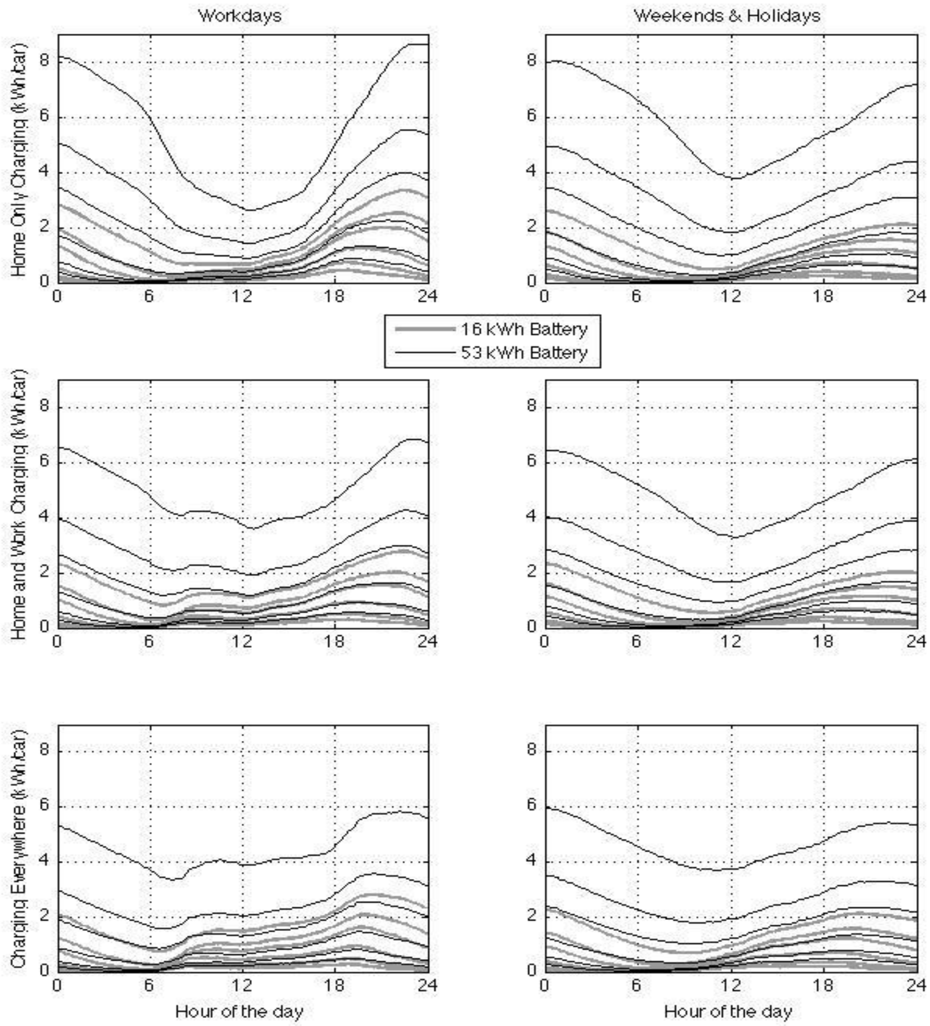


Figure 45: ESO through time for vehicles that charge immediately upon plugging in at Home Only (top), Home and Work (middle), or Everywhere (bottom). Thin black lines track ESO in vehicles with 53 kWh batteries, while the thick grey lines represent vehicles with 16 kWh batteries. Charging rates of 1, 1.5, 2, 3.3, 6, and 9.6 kW are assessed, higher power charging results in less ESpO.

Within each 24-hour period, the primary variability of ESO shown in Figure 45 is that associated with vehicles departing from and returning to plug locations. This fact can be seen by comparing the profile of ESO in for the 'Home Only' infrastructure results (top row of Figure 45) with the results of the parking location analysis shown in Figure 2. The effect of charging infrastructure is also significant, as shown by the contrast between the 'Home & Work' infrastructure model (second row of Figure 45) and the charging Everywhere infrastructure model (bottom row of Figure 45) with 'Home Only' (top row). Interestingly, more charging infrastructure increases the daytime ESO minimum, by connecting cars at daytime parking locations, but reduces the evening (and daytime average) ESO by providing more opportunities for each car to charge during the day.

Changes in the ESO resource due to vehicle design parameters are also significant. Fleets of vehicles with larger batteries provide more ESO by successfully completing more long trips and thus including some batteries in the fleet with larger quantities of ESpO, which can be seen by comparing the thin black lines for 53 kWh batteries with the thick grey lines for 16 kWh batteries. Higher power charging reduces ESO by filling it faster, shown by the successively lower values of each line type in each plot of Figure 45.

As an aggregated resource, the results presented in Figure 45 indicate that ESO varies throughout the day, and is highly sensitive to not only vehicle use patterns and charging algorithms, but also to the size of vehicle batteries and the recharging power available to such vehicles. Of interest is the fact that in general, this ESO resource is very small, such that even a vehicles with very large batteries (53 kWh, thin black lines) and with a very low average charging rate of 1 kW (top line) will rarely exceed 8 kWh per vehicle when charging is available at home only. Such an example corresponds to a 10 kW EVSE, charging with a set point S of 0, modulated according to a signal with a capacity factor f of 0.1. At higher charging rates such as 6 kW, necessary to deliver an acceptable level of vehicle substitutability, the resource will rarely exceed 2 kWh/vehicle on average. During the middle of the day, the resource drops to less than half of its peak size even if EVSEs are available at work.

An interesting feature of these results is that as charging power drops (progressively higher lines in each plot of Figure 45), ESO reaches its maximum progressively later in the evening. For very slow charging of less than about 2 kW average power for instance, the ESO resource peaks late enough that the application of this capacity to valley filling (absorbing excess energy when grid loads are light) is quite convenient. This observation leads to further questions about the benefits of changing a vehicle's charging behavior through time, and how such changes may be applied to optimize not only grid load but also the ability to provide grid services. These changes in charging behavior exist in this model in the form of charging algorithms:

The available ESO can be expected to vary with charging algorithm, since the timing and intensity of filling the batteries will be affected. The analysis used to generate Figure 45 assumes the use of Algorithm 1, in which vehicles charge right away upon being plugged in. In Figure 46, the impacts on available ESO through the day are of the 2nd set of charging algorithms are presented. These charging algorithms use the time of day as a signal for when to charge or moderate charging. Algorithm 3 in particular ('Charge at Half Rate During the Day') may therefore roughly correspond to varying battery response for both modulated charging during the day and valley filling at night. As before, the column of plot on the left is the variability of fleet average ESO through time during work days. The right plot in Figure 46 (and the two subsequent plots for the other charging algorithm groups) is the fleet average ESpO, in kWh per vehicle, available at 11pm of workdays, as a function of the battery size and home charging power of the vehicles. This parameter is of interest specifically as an evaluation of the potential of valley filling overnight. While other specific times might be marginally better suited to an evaluation of valley filling, the definition of 11pm as the start of 'night' within the charging algorithms made it the most appropriate point in time for this analysis.

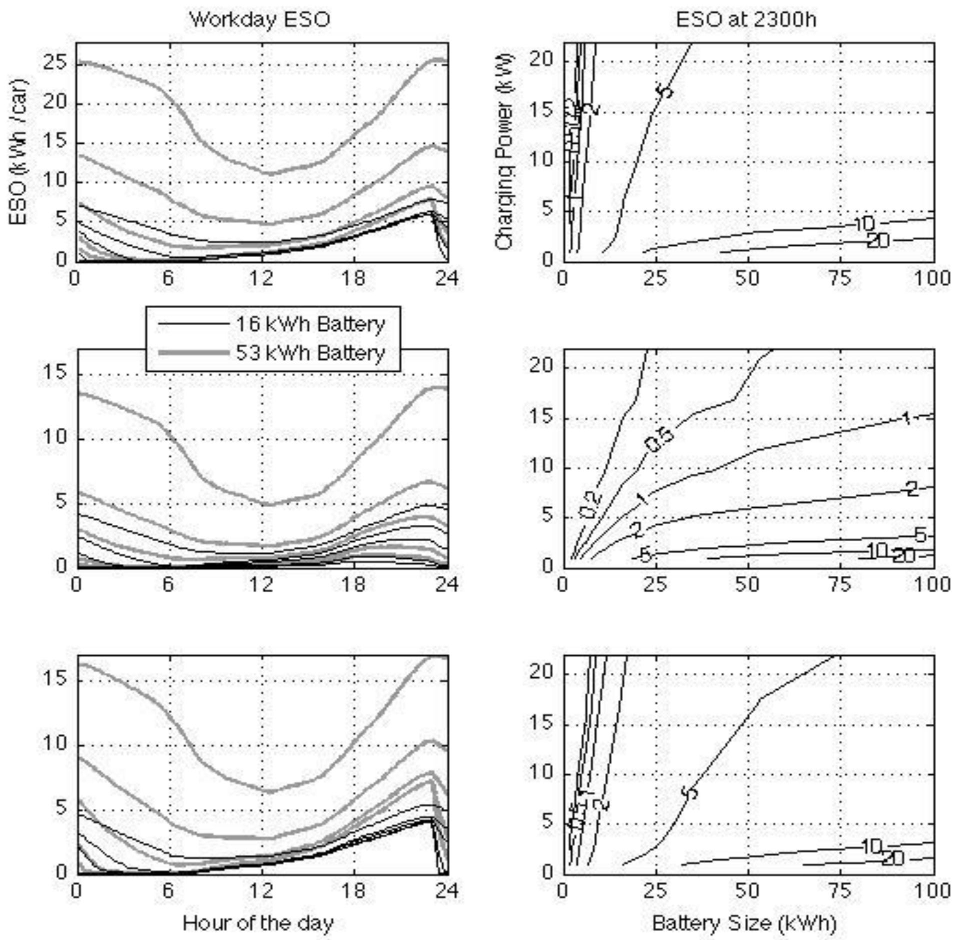
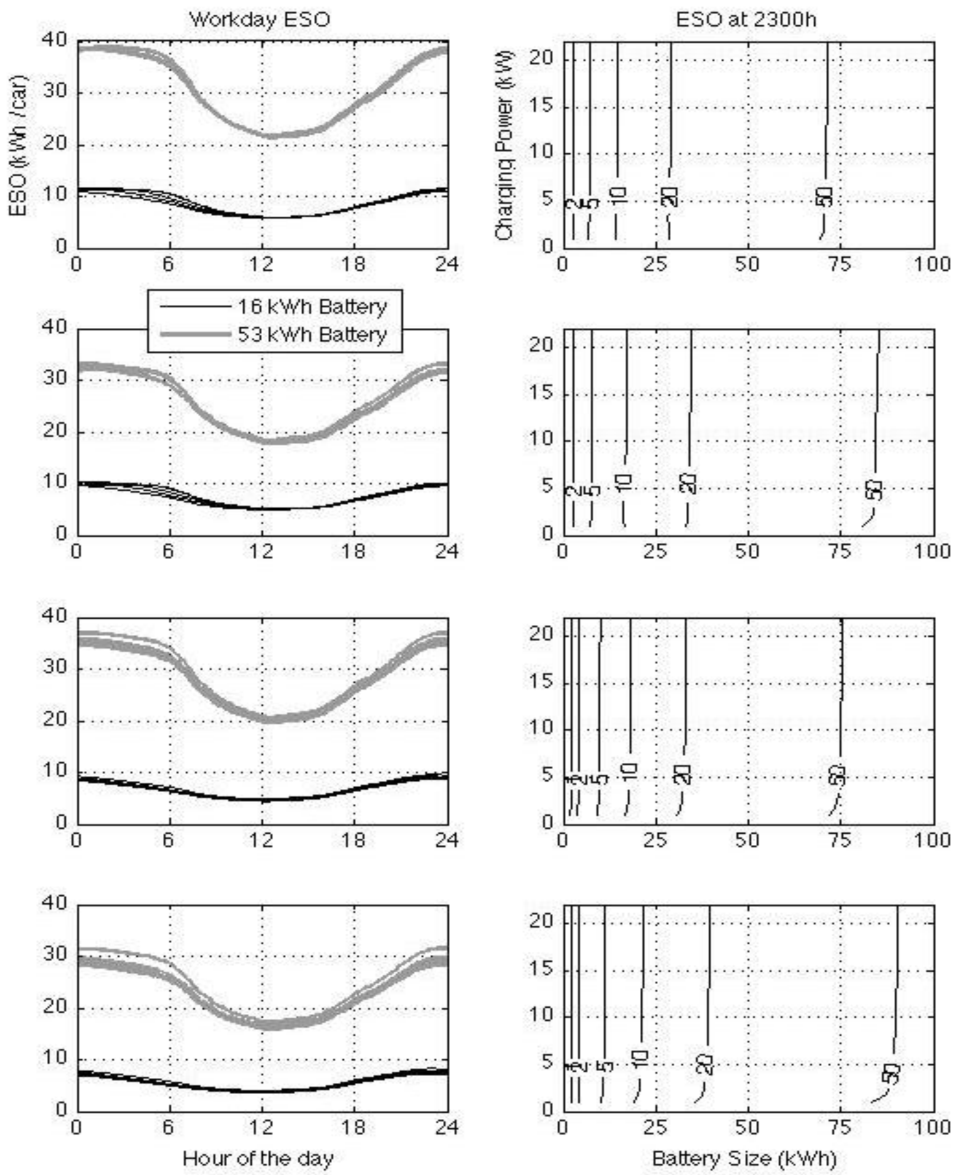


Figure 46: ESO per vehicle through time charging 'Only at Night' (top), at 'Half Power during Day' (middle), or 'To Half Battery during Day' (bottom). Maximum charging rates of 1, 1.5, 2, 3.3, 6, and 9.6 kW are assessed. Higher power charging results in less ESO. Thin black lines indicate ESO in vehicles with 53 kWh batteries, while the thick grey lines are for 16 kWh batteries. Right column shows ESO at 11 pm (kWh / vehicle) as a function of battery size and charging power.

The first row of plots in Figure 46 shows the effect of using the “Charging only at Night” algorithm, the middle row is “Charge at half rate” during the day, while the bottom row is “Charge to Half Battery” during the day. For all three of these algorithms, the daily average ESO is increased significantly compared to the results shown for the ‘Charge Right Away’ Algorithm in Figure 45. This change is particularly evident in the evening. The response in ESO to the point in time when charging (or full power charging in the cast of Algorithm 3, middle plots) resumes at 11pm is dramatic. The effect of the transition to ‘night’ in all of these is striking, and highlights the need to use 11 pm for the assessment of valley filling potential rather than later hours, when much of the ESO available at 11 pm has been filled by increased charging rates. Despite this slight ambiguity, the overall conclusion from these findings is that time-of-use based charging algorithms are very compatible with modulated charging grid services, particularly with valley filling.

In Figure 47, the ESO effects of the third set of charging algorithms are shown. Algorithms 5 and 6 (the first and second row in Figure 47) charge “At the Last Minute” at full power to be ready for upcoming trips, and reserve a 10% and 25% battery energy capacity buffer, respectively. Algorithms 7 and 8 (the third and bottom rows of Figure 48) charge ‘At a Constant Rate’ to prepare for upcoming trips, again with a 10% and 25% energy buffer. In the left column the 24 hour ESO profiles over workdays are shown. In the right column, the effect of battery size (x-axis) and home charging rate (y-axis) are shown on ESO at 2300.



Workday ESO
ESO at 2300h
ESO (kWh /car)
Charging Power (kW)
16 kWh Battery
53 kWh Battery
Hour of the day
Battery Size (kWh)

Figure 47: ESO per vehicle available through time using 'At the Last Minute' (top two rows of plots, with 10% & 25% energy buffer), and 'At Constant Rate' (bottom two, with 10% & 25% energy buffer) charging algorithms. Charging rates of 1, 1.5, 2, 3.3, 6, and 9.6 kW are assessed. Thin black lines indicate grid connected empty space in vehicles with 16 kWh batteries, while the thick grey lines are for 53 kWh batteries. Right column shows ESO at 11 pm (kWh / vehicle) as a function of battery size and charging power.

What is immediately evident in Figure 47 is that the effect of charging power on ESO is all but eliminated, a result consistent with the fact that default states of charge, rather than available charging power, drive much of the charging behavior. In Figure 47, it is also evident that trip-predicting charging algorithms dramatically increase average ESO levels. In the four algorithms described here, the default state of charge is either 10% (first and third rows of plots) or 25% (second and last rows). Note how in the first and third sets of plots in Figure 47, the 24-hour workday plots (left plots) reach a maximum of almost 40 kWh per vehicle, for vehicles with 53 kWh batteries (grey lines; 53 kWh less a 10% buffer leaves 48 kWh as ESO for those vehicles online), whereas in the second and last rows of plots ESO only reaches about 30 kWh per vehicle (a 25% buffer leaves 40 kWh). The result of low default states-of-charge is that there is always lots of ESO, storage capacity that could be put to use for grid services such as valley filling or Reg Down.

In Figure 48 the ESO responses to the final set of charging algorithms are shown. Algorithms 9 and 10 (the first and second row in Figure 48) charge the battery after the last trip of the day so as to be full each morning, with incidental daytime charging when needed. Algorithm 10 adds a 10% battery energy buffer. Algorithms 11 (bottom rows of Figure 48) charges only when travel needs in the next 24 hours exceed current energy stores, mimicking observed driver behavior. In the right column, the effect of battery size (x-axis) and home charging rate (y-axis) are shown on ESO at 11 pm, the start of 'night-time' as defined in the model.

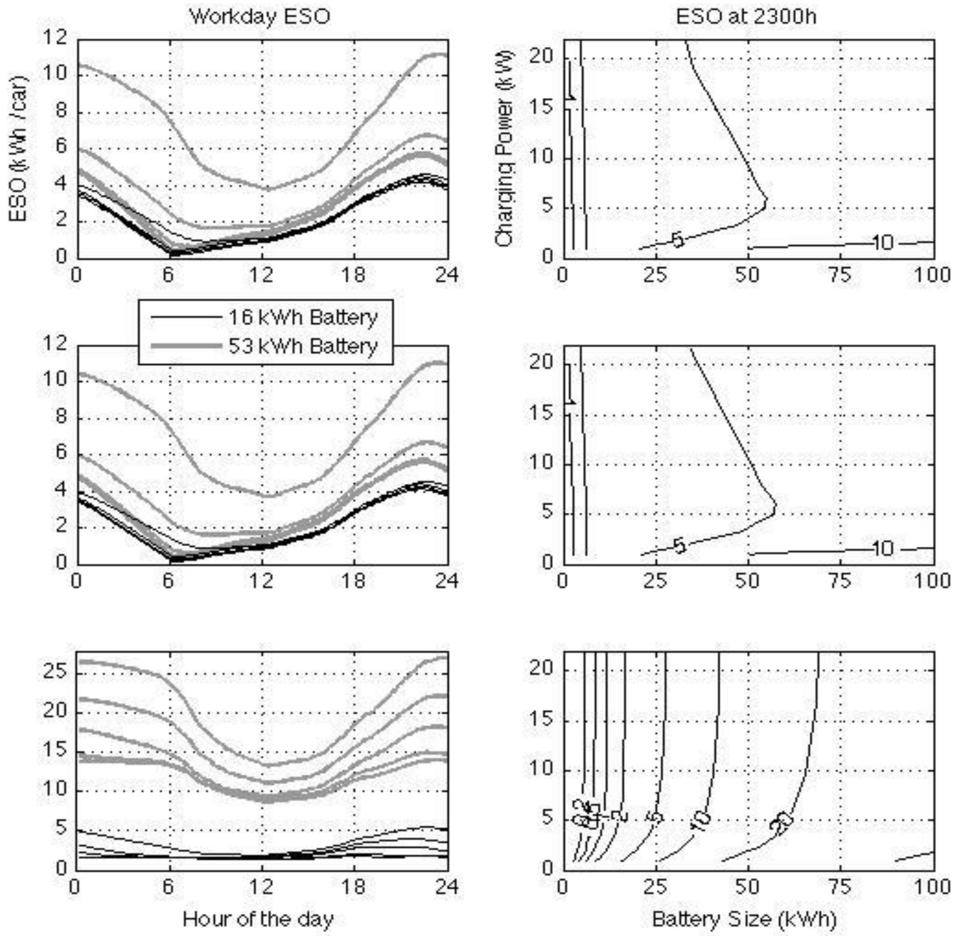


Figure 48: Average ESO per vehicle available through time using 'Overnight, Incidental during the Day' (top), 'Overnight, Incidental during the Day with 10% Energy Buffer' (middle), or 'Charge Fully When Needed' (bottom) charging algorithms. Average charging rates of 1, 2, 3.3, 9.6 and 16.8 kW are assessed. Higher power charging results in less ESO. Thin black lines indicate ESO in vehicles with 16 kWh batteries charging, while the thick grey lines are for 53 kWh batteries. Right column shows ESO at 11 pm (kWh / vehicle) as a function of battery size and charging power.

Algorithms 9 and 10, the charging algorithms which prioritize overnight charging (first and second rows of plots in Figure 48) show their hybrid nature in maintaining levels of ESO very like those due to ‘Charge Right Away’ algorithm seen in Figure 45 for much of the day, but with slightly greater accumulated ESO in the evening, like the second set of algorithms shown in Figure 46. By 11pm when the ESO data for the right plots are sampled, the higher values of ESO in Figure 48 compared to those in Figure 46 suggest that most vehicles are plugged in a charging, such that vehicles with higher charging power (higher in the y-axis direction on the right plots) have reduced ESO. A minimum ESO, and thus a minimum in the amount of overnight valley-filling vehicles could do, occurs at about 6 kW charging power. At charging rates greater than about 6 kW, presumably less incidental charging took place late in the day, so vehicles arrived at home with lower SoC (more energy space), but since most started charging before 11 pm, those with very low charging power (below 6 kW) retain more ESO at 11 pm because it hasn’t had time to fill.

In the final charging algorithm, the workday 24 ESO profile plot on the left shows that increasing charging power (sequentially lower lines) only reduce ESO to a point. That point is defined by the interplay of trip length distributions and parking time distributions, as well as the 10% energy reserve included in the algorithm definition. As with the third group of charging algorithms, which also use predictions of upcoming travel patterns, Algorithm 11 shows that trip prediction tends to leave far more ESO in the fleet.

The value of valley filling to a vehicle owner can be assessed from Figure 45 through Figure 48 as the ESO for a given vehicle configuration multiplied by the price differential between peak and off peak energy rates. As an example, a Nissan Leaf-like vehicle, with a 24 kWh battery and 3.3 kW charging, using Algorithm 11 would have, on average, about 7 kWh of battery to fill each night. If a utility offered a time of use rate in which peak price was 20 ¢/kWh, while off-peak pricing was 10 ¢/kWh, then such vehicle could charge overnight for a nightly energy savings of about 70¢, or an annual savings of $250.

9.5 V2G - GIV Service Potential; The Value of Backfeeding

The result presented in section 9.4 for modulated charging grid services and valley filling, when compared to the analytical conclusions found for the various charging scenarios in section 9.2, reaffirm that the value proposition in vehicles providing grid services is significantly augmented by the ability to backfeed electricity. In this section, the value potential of V2G will be assessed from the travel data.

9.5.1 Energy Stored in Plug-In Vehicles Available Online

While the grid support services thought likely to be of interest to vehicle owners in the near term are capacity based and (more or less) energy neutral over short time scales (Kempton et al. 2012, Kempton et al. 2008), other services exist that, are not energy neutral but draw power only for short periods, thus allowing pre-charge before and recovery afterwards, so may be of interest if sufficiently remunerative (Kempton, Tomić 2005a, Lachs, Sutanto 1995, Millner et al. 2010). Three examples are spinning reserves, peak shaving, and capacity charge avoidance. While spinning reserves is an energy consuming service (from the point of view of the car), and tends to be priced at less than half the price of frequency regulation, it poses the potential advantage of requiring far less energy throughput. Thus, if battery degradation by cycling is of concern, spinning reserves may be deemed preferable because it may degrade the battery less (Peterson, Apt & Whitacre 2010). The service with both the largest and most universal market, and the greatest risk to be energy throughput intensive is peak shaving, which corresponds conceptually to nighttime valley filling discussed in section 9.4. Where valley filling consists of preferentially buying cheap energy overnight (and does not require V2G capability), peak shaving involves selling excess energy back to utilities at peak prices. A third example, which could be limited both by power and energy, is capacity charge avoidance for industrial customers (Millner et al. 2010). For such services, the metric of interest (or one of the metrics of interest) in evaluating a GIV storage resource is energy available through time. Since this will scale linearly with the size of the V2G fleet, the stored energy online per vehicle is a more useful normalized quantity. This parameter, which will be referred to as 'Mean Stored Online Energy' (MSOE) will also vary with the different scenarios modeled in this research, and is investigated here.

For grid support services reliant on, or potentially limited by energy availability as well as power capacity, it is important to know how vehicle and infrastructure design affect the quantity of MSOE, the stored energy resource. Following the graphic conventions of Figure 24 in Chapter 8, Figure 49 shows the time-varying energy resource associated with Grid interactive EVs. The cumulative amount of energy in the fleet of vehicles is evaluated for each of the three infrastructure scenarios of i) EVSEs available only at home, ii) EVSEs available at home and at work parking locations, and iii) EVSEs available everywhere vehicles park for more than 30 minutes, and is then normalized by the number of vehicles in the study through time. In this analysis it is assumed that any available EVSE and all vehicles can supply both charging and discharging capacity, and have a connection to an information stream associated with grid management.

The quantity of stored energy in the vehicles that are connected to the grid is plotted as a function of time in Figure 49. The analysis examines each 10-minute time-span, separately averaging those for workdays, of which there are 251 and those for weekend days and holidays, of which there are 110, consistent with the methodology applied in previous sections. In each plot there are two sets of lines, which present the average online energy for two charging rates (2 kW and 17 kW, as before in thin black and thick grey lines respectively). Because the primary dependence of MSOE is battery size, each set of lines presents the online energy for six different vehicle battery capacities, 6, 16, 24, 35, 53, and 100 kWh per vehicle, respectively. These 6 capacities are plotted in descending order in all scenarios in Figure 49. Note that in the previous section, multiple charging powers were plotted for just two battery sizes, while in this section multiple battery sizes are plotted for just two charging powers.

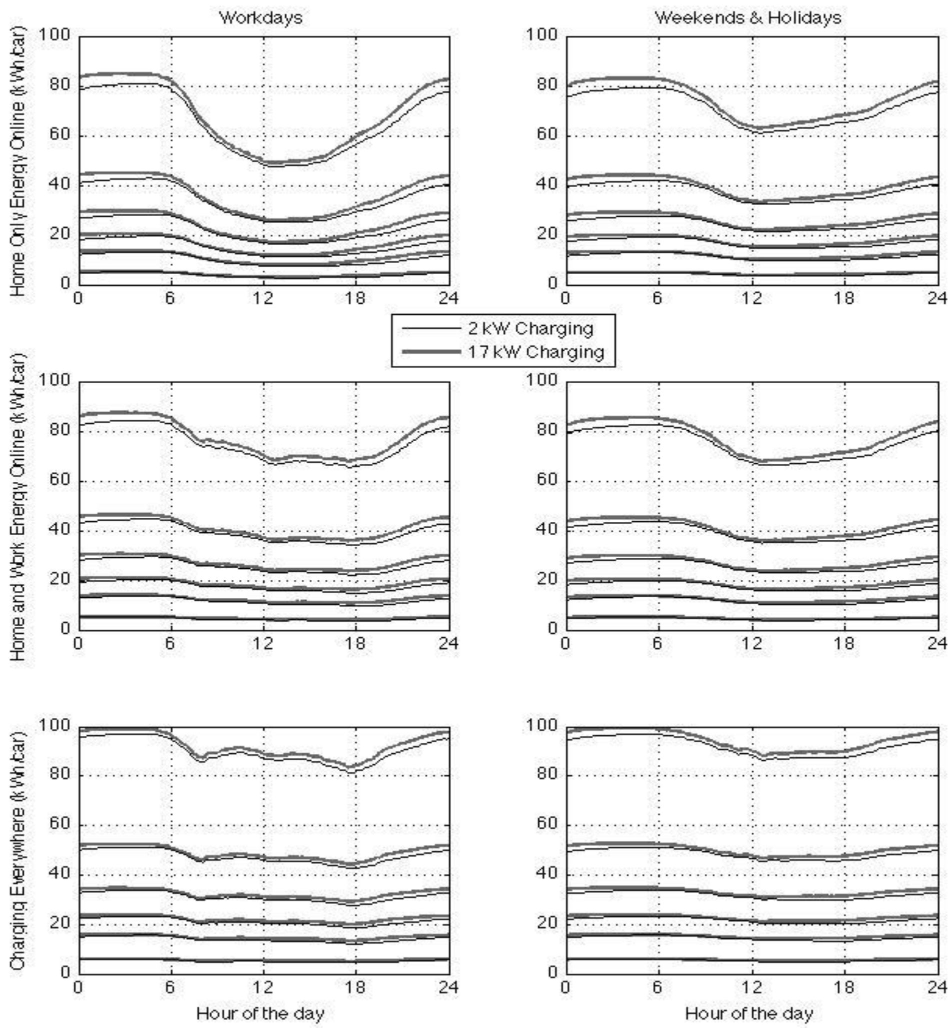


Figure 49: MSOE throughout workdays (left column) and weekends and holidays (right column) for vehicles charging at home only (top row), home and work (middle row), or everywhere (bottom row). Line pairs, from top to bottom, represent vehicles with 100, 53, 35, 24, 16, and 6 kWh of energy storage in vehicles with 2kW (grey lines) or 17 kW (black lines) charging.

Figure 49 shows that, more than any other factor, the battery capacity of the vehicle determines how much MSOE there is at any time. For instance, the highest grey line in each plot, indicating the energy online in a fleet of GIVs with 100 kWh batteries, approach 100 kWh/vehicle when plugs are available everywhere (bottom row), and it's the middle of the night, and can drop as far as 50 kWh/vehicle average if charging is available only at home (top, left plot). The next most capable vehicles, which have 53 kWh batteries, can never provide more MSOE than just under 53 kWh per vehicle, and will on average provide as little as ~25 kWh/vehicle in the middle of workdays.

The results presented in Figure 49 are not surprising. The amount of energy online tracks the previously assessed parked population closely (Figure 2), with a small time delay associated with recharging upon plugging in. The magnitude of the time delay, however, is small both in time (x-axis) and in energy (y-axis) compared to the variability in total stored energy online associated with vehicles being away from charging infrastructure. The MSOE resource itself, as clearly shown in Figure 49, has little dependence on charging rate (grey vs. black lines), and a very strong dependence on battery capacity.

The places where charging power does have an effect are indicated in the plots by the areas where grey and black line pairs diverge. In those conditions, the act of recharging produces a time delay between vehicle presence on a plug and available energy. Thus workday evenings, which the analysis presented in section 8.2 indicated had the highest charging loads, shows the greatest discrepancy in total stored energy online between slow and fast charging. Even there, however, that difference is small in comparison with both inter-hour fluctuations in resource associated with departure from and arrival at plugs, and in variations due to different battery size. For this reason, a separate analysis of the effects of charging power on total stored energy online, analogous to Figure 24 in section 8.2, will not be performed.

It should be noted that the plotted lines in Figure 49 represent the total stored online energy per vehicle. Not all of this energy will be available to grid operators. The fraction of MSOE that, on average, vehicle owners will be willing to part with at any given time will depend on several factors other than the resource evaluated here. These factors may include any combination of i) the price being offered (eg. the spot market price of electricity), ii) the vehicle owner's knowledge of, or uncertainty about, the timing and distance of upcoming travel, iii) the ease of travel adaption in each specific case, iv) the desire for a 'range buffer', and v) concerns about wear due to battery cycling. The interaction of these factors, some of which are specific to individual vehicle owners and some of which will be influenced by the structure of the electrical market in which the vehicles are participating, make the data delivered by this model a theoretical maximum. However, knowledge of this maximum, combined with knowledge of trip frequencies throughout the day and results of investigations into the desire for a range buffer (Turrentine, Kurani 1998, Anegawa 2009, Cocron et al. 2011, Franke, Krems 2013), form a foundation for assessing the resource as it varies through time.

9.5.2 The Effect of Charging Algorithm on Stored Energy Online

Charging algorithm will have a significant effect on the amount of energy in vehicles' batteries, as they did on energy space online (ESO) evaluated in section 9.4. Moreover, the timing of energy consuming services such as capacity charge avoidance and energy arbitrage is less arbitrary than inter-hour variations in the price of capacity services, making knowledge of the time-dependent nature of MSOE that much more important. For this reason, an analysis of the effects of charging algorithms, and the inter-hour changes in online energy are of great interest. In this section the effects of charging algorithm are described by plotting the change in online energy through time for each algorithm. In parallel with the previous analysis of the effects of charging algorithms, the algorithms are divided into four groups based on the information used to determine when charging takes place. As before, the first 'group', is the 'Charge Right Away' algorithm, and is thus a repetition of the top two plots in Figure 49, presented here for completeness:

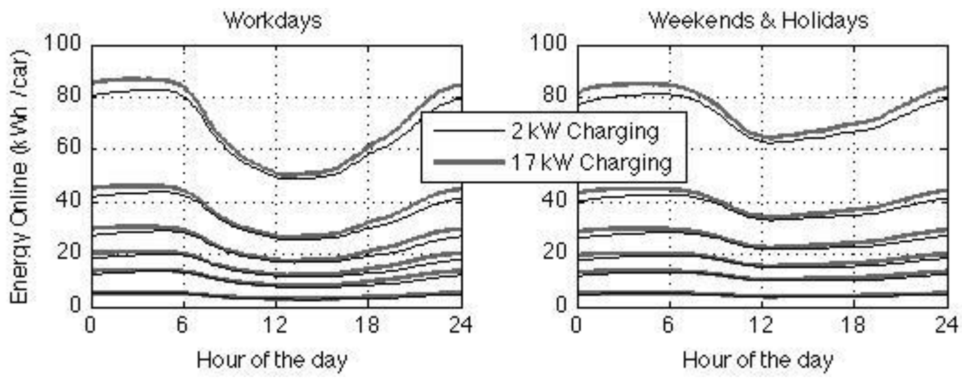


Figure 50: MSOE on workdays (left plot) and weekends or holidays (right plot) when charging using Algorithm 1; Charge Right Away. For GIVs with (in descending order) 100, 53, 35, 24, 16 and 6 kWh batteries, and either 2 kW (black lines) or 17 kW (grey lines) charging power capacity.

Algorithm 1, 'Charge Right Away', is the simplest case for vehicle operation, and mimics the behavior of almost any other rechargeable device; when you plug it in, it starts charging. This results in the highest possible state of charge, and thus the highest value of MSOE, at any given time. This fact will be apparent in contrasting Figure 50 with the next 3 figures, associated with the more restrictive charging algorithms.

The second set of algorithms use time-of-day information to modulate charging behavior. The dramatic effect Algorithms 2, 3, & 4 have on charging load through time was presented in section 8.6. The effect they have on energy availability is presented in Figure 51.

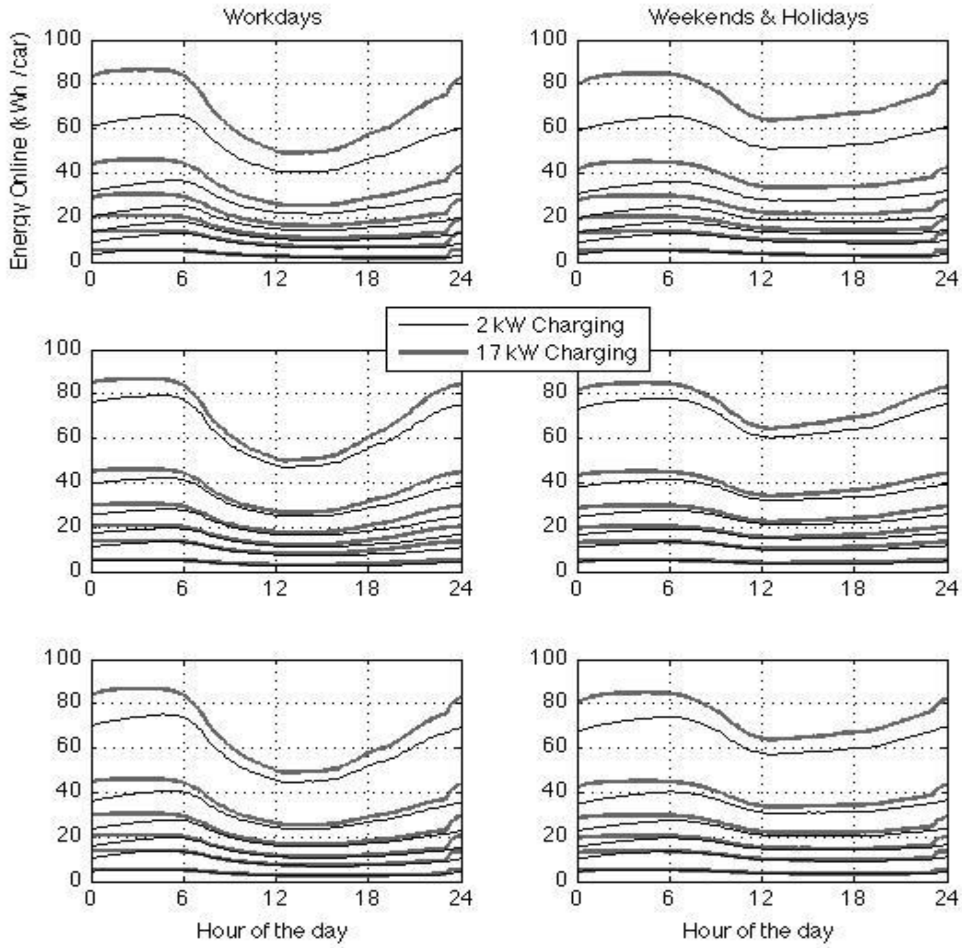


Figure 51: MSOE on workdays (left column) and weekends or holidays (right column) when charging at 'Night Only' (top line), at 'Half Power during the Day' (middle line), and 'To Half Battery during Day' (bottom line). For GIVs with (in descending order) 100, 53, 35, 24, 16 and 6 kWh batteries, and either 2 kW (black lines) or 17 kw (grey lines) charging power capacity.

Charging only, or even primarily at night, the effects on MSOE shown in Figure 51, are moderate for the 17 kW charging power scenario. A visual comparison of the highest grey lines in each of the plots in Figure 51 (17 kW charging, 100 kWh batteries) to those in Figure 50 indicate only modest reductions in MSOE. The changes that are perceivable occur in the afternoon and evening up to midnight, when it is reasonable to anticipate diminished states of charge, after hours of restricted charging activity have left the batteries of at least some individual vehicles depleted. The moderate visual difference however should not be neglected, as the vertical axis range is compressed to include the 100 kWh battery vehicles. A change of 10 kWh, or just 10% of the y-axis range in Figure 51, is very significant from the point of view of vehicle trip readiness. Where range buffer concerns may limit the amount of energy a vehicle owner may by willing to sell back to the grid, the difference of 10 kW, or 36 miles of driving range at our assumed 280 Wh/mile, could be quite significant.

For the lower charging power scenario also presented in these plots, in which vehicles can charge at a maximum rate of 2 kW, the effects of restricting daytime charging are much more dramatic. In all three charging algorithm cases, they get progressively more dramatic as battery sizes increase. For instance, examine the workday (left) plot of Algorithm 3; ‘Half Rate During the Day’ (middle line in Figure 51), the MSOE for the 2 and 17 kW charging vehicles converge at about midnight for the smallest, 6 kWh battery vehicles, at about 3 am for the next larger 16 kWh vehicle, at about 4:30 am for the 24 kWh, and not until after vehicles start leaving for work at 6 am for the three larger battery sizes (35, 53, and 100 kWh), if at all.

Thus, while apparently unimportant if vehicles charge immediately upon plugging in, for some time-of-day based charging algorithms, charging rate is very important to a vehicle's ability to participate in energy-based V2G markets. Because the concept of 'charge right away' is anathema to several of the possible grid stabilizing services under consideration, this conclusion is significant.

The third set of charging algorithms employs knowledge of upcoming trips and charges either 'At the Last Minute' (Algorithms 5 & 6) or 'At a Constant Rate' (Algorithms 7 & 8), with an energy buffer of 10% (Algorithms 5 & 7) or 25% (Algorithms 6 & 8) of battery capacity. The expected result of all of these algorithms is that battery states of charge, and thus total stored energy online, will fluctuate between the range buffer level and the level necessary for each successive trip. These states of charge will in almost all cases be far lower than the full capacity of the battery, so it is reasonable to anticipate MSOE values far lower than were found in any of the other charging algorithms. The results of this analysis are presented in Figure 52.

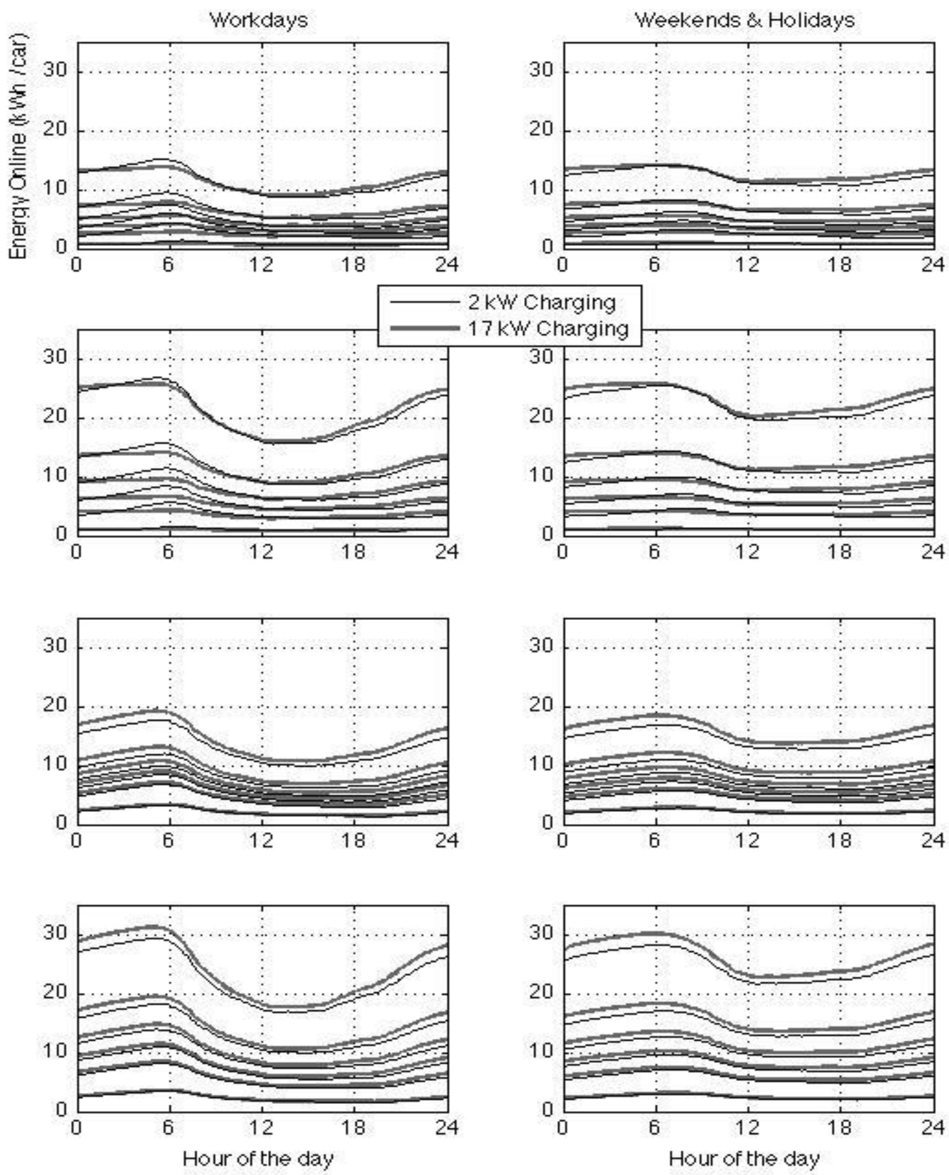

Workdays
Weekends & Holidays
Energy Online (kWh /car)
2 kW Charging
17 kW Charging
Hour of the day
Hour of the day

Figure 52: MSOE per car on workdays (left column) and weekends or holidays (right column) when charging using 'At the Last Minute' with a 10% or 25% buffer (top two lines), and 'At a Constant Rate' with a 10% or 25% buffer (bottom two lines). For GIVs with (in descending order) 100, 53, 35, 24, 16 and 6 kWh batteries, and either 2 kW (black lines) or 17 kw (grey lines) charging power capacity.

Note that in Figure 52 a dramatically foreshortened y-axis scale was used to display the results. In these four algorithms the 'normal' state of charge fluctuates between 10% (Algorithms 5 and 7, the 1st and 3rd sets of plots in Figure 52), or 25% (Algorithms 6 and 8, the 2nd and 4th sets of plots), and the energy needed for the next trip. States of charge of individual vehicles will also periodically drop below the buffer levels of 10 and 25%, when parking time prior to long trips is insufficient to take enough energy on. As a result, the MSOE in vehicles' batteries is systematically far lower than those found for the other charging algorithms. While the effects of these algorithms on grid loading (shown in Figure 31) appear very desirable for avoiding peak-coincident load, these results suggest that if GIV energy services are under consideration, or if energy availability may limit capacity services, this set of charging algorithms must be either substantially modified or avoided altogether.

The final set of charging algorithms are those that use both the time of day and knowledge of upcoming travel to determine charging rates. In the first two rows of plots, Algorithm 9 & 10 begin charging after the last trip of the day, and charges at full power until the battery is full, until daytime electric rates kick in (at 6 am in this model), or until the first trip of the next day begins, whichever comes first, and charge incidentally during the day for upcoming trips when when necessary. Algorithm 10 adds a 10% battery energy buffer. Algorithm 11, “Charge When Needed”, charges without regard to time of day, if more energy is needed for upcoming travel in the next 24 hours, based on current state of charge and expected travel. The results of these three analyses are shown below in Figure 53.

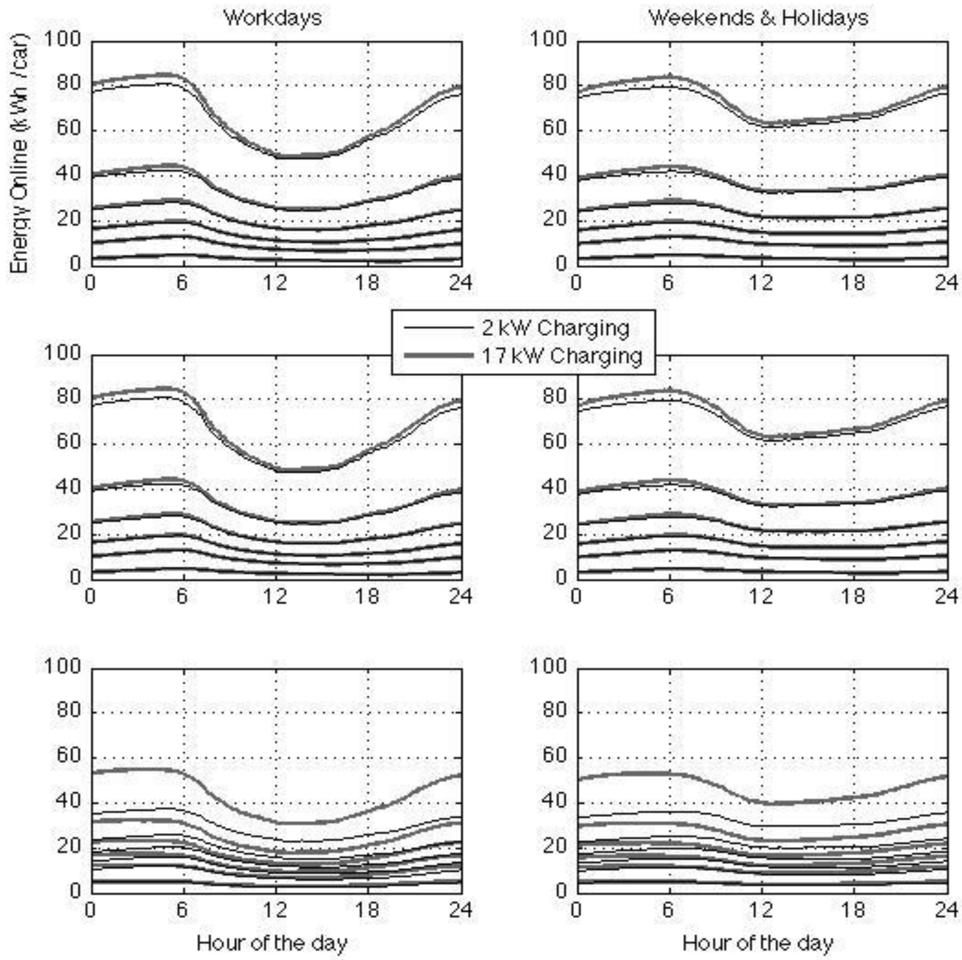


Figure 53: MSOE per car on workdays (left column) and weekends or holidays (right column) when charging to 'Full each morning, incidental for trips' (top line), 'Full each morning, incidental for trips w/ 10% Buffer' (middle line), and 'When Next Day's Travel Exceeds Range' (bottom line). For GIVs with (in descending order) 100, 53, 35, 24, 16 and 6 kWh batteries, and either 2 kW (black lines) or 17 kw (grey lines) charging power capacity.

Figure 53 shows energy availability patterns for Algorithms 9 & 10 are strikingly similar to those for Algorithm 1; 'Charge Right Away'. Algorithm 11 on the other hand is distinct among this section in not only showing a dramatically lower general level of MSOE (a characteristic which it shares with Algorithms 5 through 8, which also evaluate upcoming travel needs), but also in showing a strong dependency on charging rate.

9.5.3 Energy Markets; Power Capacity Available Online

Analysis in section 9.2 corroborated previous research eg. (Kempton, Tomić 2005a) in suggesting that energy neutral capacity markets may offer the greatest financial benefit to participating vehicle owners. The fraction of time spent online not charging discussed in section 9.3.3 can be translated into a potential value for vehicle owners and utility managers by multiplying the available idle time by the available power. This parameter was described in section 9.2 by the equation $P(T\text{-}E/P)$, which was simplified to $PT\text{-}E$ where P is charging and discharging power capacity, T is total time spent at a plug, and E is energy used for transportation. Thus spending 1 more hour at a plug than is necessary to replenish the battery, and being able to absorb or supply 6 kW of power, means that that car has the potential to deliver 6 kW-hr of (energy neutral) grid services. In the following three plots, therefore, iso-graphic lines show contours of constant kWh-hr of potential grid services. It should be noted that this, as with other parameters presented in this chapter, is a theoretical maximum for each configuration of vehicle. Uncertainty in trip planning, opting not to plug in on some occasions, the driver opting out of market participation, or other factors may reduce this resource. The units on the isographic lines in Figure 54 are therefore theoretical potential MW-hr of grid service per year, from vehicles that plug in at home locations only.

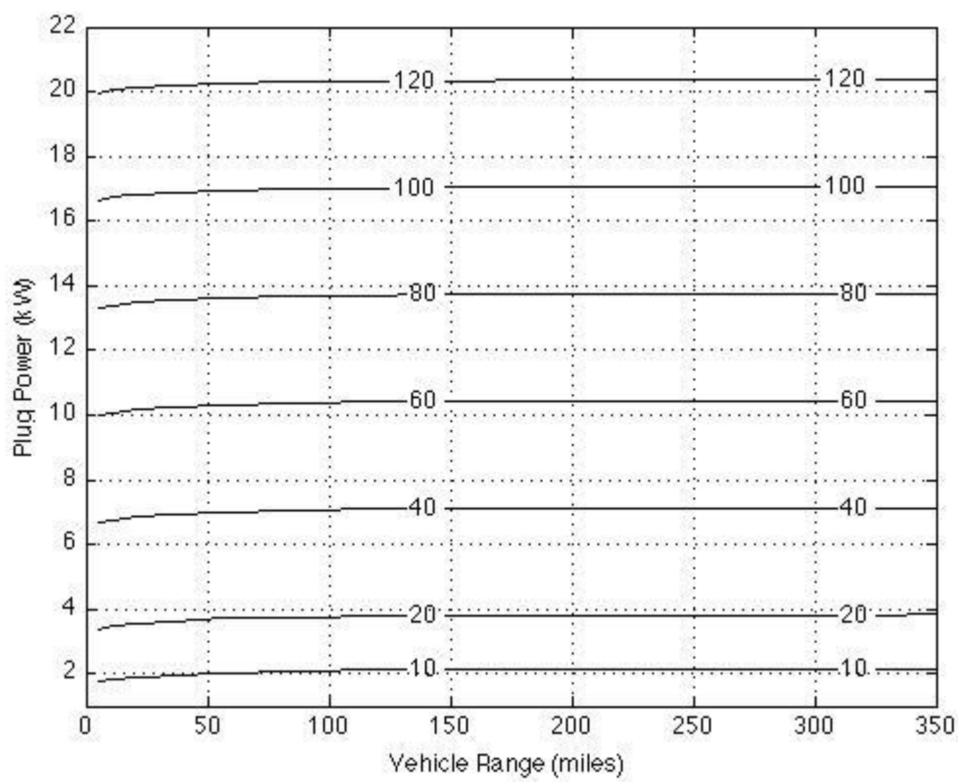


Figure 54: Potential MW-hours per year, per vehicle, of energy neutral grid service when V2G-ready EVSEs are located at Home parking locations only.

Comparing Figure 54 to Figure 41, the compounded effect of faster charging is evident: Because vehicles can replenish their batteries more quickly, faster charging leaves each vehicle more time for grid services, and because the power capacity itself is the commodity being sold, higher power charging delivers more to the market on the hours when each vehicle is available. As a result, the effect of battery size, indicated by vehicle range in Figure 54, is negligible in comparison; throughout the entire range of analysis, the benefit of faster charging dominates. Also of note is the fact that the value (the quantity of potential service provided), does not exhibit 'diminishing returns' on higher charging power to nearly the same degree that other parameters examined previously in this research (vehicle substitutability, charging load and ESO); the number of MW-hr/year available continue to rise very nearly in proportion to charging power.

The corresponding results for vehicles that can charge both at home and at work are presented in Figure 55.

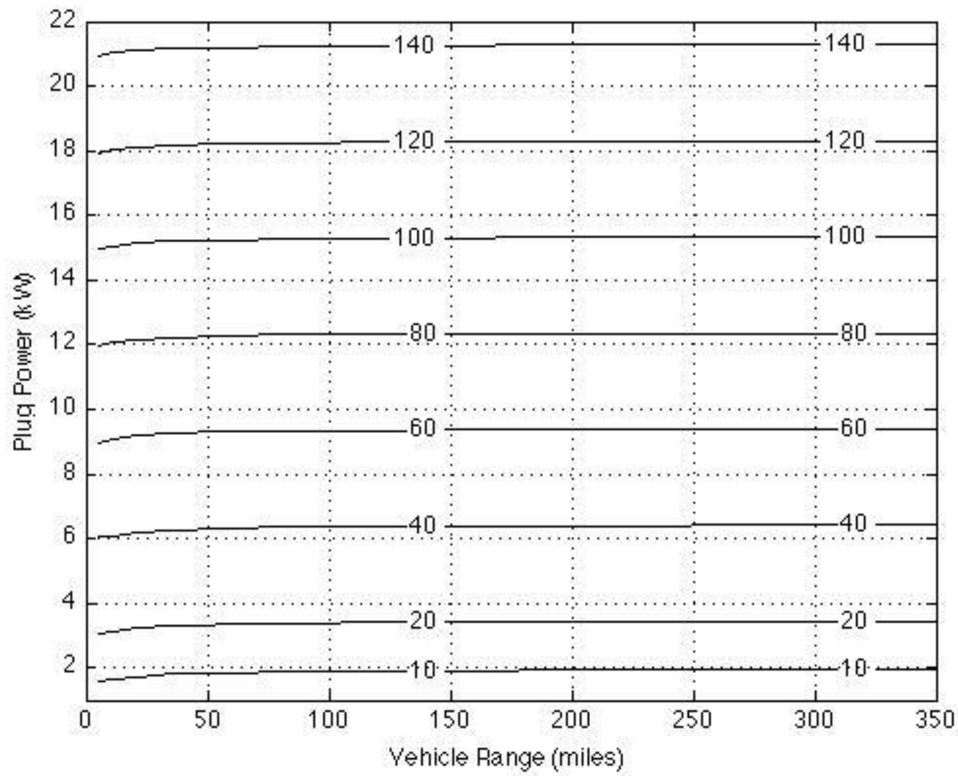


Figure 55: Potential MW-hours per year, per vehicle, of energy neutral grid service when V2G-ready EVSEs are located at both Home and Work parking locations.

While it was clear in section 9.3.3 that adding more charging locations would impact the amount of idle time vehicles could spend at plugs. By comparing Figure 55 to Figure 54 it is evident that, again, it is the charging power that drives this value proposition. While adding at-work charging provided a 13% increase in service time for a vehicle with a 6 kW charger (71% vs. 63% of the year for long range EVs), by comparing Figure 55 to Figure 54 we see that the same 13% gain in MW-hr service (from 37 to 42 MW-hr) could be realized from just a 2 kW increase in charge power, from 6 kW to 8 kW (Figure 54).

With charging infrastructure at every parking location, the gains in available time seen in section 9.3 were larger. Figure 56 depicts the service potential ($PT - E$) in MW-hr/year that EVs could provide if V2G-capable charging infrastructure were available at every parking location. It is included for completeness, though as previously stated, widespread, high power V2G at public charging locations seems unlikely in the near or medium term.

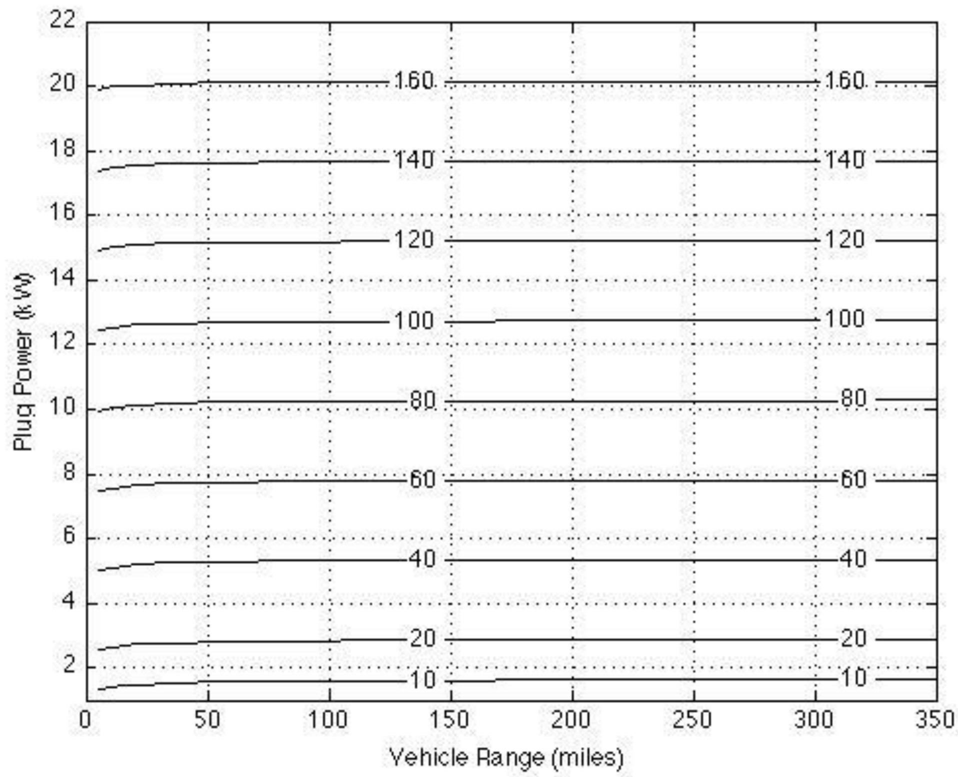


Figure 56: Potential MW-hours per year, per vehicle, of energy neutral grid service when V2G-ready EVSEs are located at every parking location.

The amount of possible service is greatest with charging in all locations, shown by the results of section 9.3.3 and Figure 23. Nevertheless, the large effect of charger power on service capacity, and thus total value, still means that the effects of more charger locations are still easily matched by relatively modest increases in charger power.

The metric presented in this section is two steps removed from an evaluation of the potential remuneration of vehicle owners for providing this service. Those two steps are i) multiplying the results presented here by the value of the service being provided, and ii) an estimate of the fraction of that market price that is transferred to vehicle owners rather than aggregators or other service providers. The former will vary significantly between electrical jurisdictions and specific markets, and the later is yet well established.

Chapter 10

CASE STUDY OF GRID STORAGE; THE POTENTIAL TO RETIRE COAL GENERATION IN NOVA SCOTIA, CANADA[25]

One of the most compelling promises of GIVs is the hope that energy storage will facilitate the integration of intermittent renewable energy resources and the displacement of dirty and non-renewable fossil energy. In this chapter the potential for storage and variable renewable generation to facilitate the retirement of aging coal-fired generation in Nova Scotia Canada, is evaluated. Nova Scotia is of interest because i) it relies heavily on imported coal for its current electricity supply, ii) it has an outstanding wind resources, both on land and in near-shore areas, iii) Nova Scotia's legislature has enacted ambitious renewable energy targets, and iv) the electrical system in Nova Scotia is connected only weakly to the rest of the North American grid, making it a highly relevant case-study for integrating intermittency. The model analysis and results presented in this chapter are based on two papers published by the author (Pearre, Swan 2013b, Pearre, Swan 2013a. With permission from ASCE).

In the first section, 10.1, some background about the energy and political landscape of Nova Scotia is presented. Section 10.2 describes the methodology used in the

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[25] This chapter draws from two published papers titled "An Extensible Electricity System Model for High Penetration Rate Renewable Integration Impact Analysis" and "Renewable electricity and energy storage to permit retirement of coal-fired generators in Nova Scotia" (Pearre Swan 2013a, Pearre Swan 2013b).

evaluation, which includes additional background and a description of data sources. In section 10.3, the energy storage model is introduced and described. Results of the analysis are presented in section 10.4. Section 10.5 elaborates on and presents a discussion of the significance of the results and how they apply to real questions being faced by energy planners in Nova Scotia. Finally, in section 10.6 conclusions drawn from this case study are presented.

10.1 Introduction; The Electric System in Nova Scotia

Recent legislation in Nova Scotia, Canada require the electricity utility to provide 25% electricity from renewable sources by year 2015 and require further regulations for 40% renewables by year 2020 (Nova Scotia Department of Energy 2011, Office of the Legislative Counsel 2007). Because of current trends as well as growth projections, the majority of renewable electricity at these milestone years expected to come from wind turbine generators (WTG). The inherent variability in these particular renewable resources, discussed in Chapter 1, will continues to require fossil-fueled generator capacity during periods of low variable renewable resource availability, as well as increasing the required conventional generator ramp-rates (e.g. WTG power decreasing as end-use demand increases, dispatchable generation must increase power output quickly to maintain system voltage). In counterpoint to this drive to increase renewables, the Canadian Government has pending regulations to retire old coal-fired generators (Government of Canada 2011) which currently provide 57% of electricity in Nova Scotia (other fossil-fuels account for an additional 26%) (Statistics Canada 2009, Nova Scotia Power 2012).

Energy storage, discussed in section 1.3, can in principle be used to reduce or eliminate the reliance on fossil-fueled generators to back-up variable renewable electricity generators (Budischak et al. 2013). Storage accomplishes this task by temporal decoupling of generation from demand, and in most cases by having a very high ramp-rate capability. Through the creation of an hourly time-step model, this study examines the peak demand and ramp-rate relationships of wind and coal-fired electricity generators, and proposes storage of sufficient capability to allow for increased WTG capacity while retiring a large coal-fired generator.

For Nova Scotia, with a relatively small interconnection to the northeast electrical system and spatial distances limited to 500 km, transmission within the province (refer to section 1.2 and (Dvorak et al. 2012)) would be an insufficient solution for leveling wind energy, while building a higher-capacity interconnection would be very costly. This effort models a storage system, envisioned as the distributed batteries of GIVs.

10.2 Methods

The fundamental data requirements for this energy storage analysis are i) the time-dependent provincial WTG power during the provincial Renewable Electricity Plan milestones years 2015 and 2020, ii) an evaluation of total provincial time and weather dependent electricity demand in those same years, and iii) the difference between the two, which represents the power that must be supplied by storage or generation other than wind. It should be noted that in this analysis, wind power production is take to the only supply-side independent variable, so these other generators include fossil-fuels, dammed or 'run of the river' hydro (some of which are dispatchable and some of which are not), biomass, and non-dispatchable tidal. In addition, interruptible load mechanisms allow the electricity utility to shut-down large end-users other than GIVs (e.g. mills) when total demand approaches system generating capacity. Provincial import/export capacity with the northeastern electricity grid was not considered as it is likely that adjacent jurisdictions will be experiencing similar peak demand and ramp-rate issues caused by variable generation energy developments. A provincial energy model to evaluate these effects has been created in MATLAB.

10.2.1 The WTG model

To characterize the variability and resource diversity of wind in Nova Scotia, seven regions within the province were identified where WTG development is taking place. These groupings were based on i) existing WTG installations, ii) geographical factors such as topography and shoreline, and iii) proximity to high-capacity transmission lines. The groupings can be seen in Figure 57.

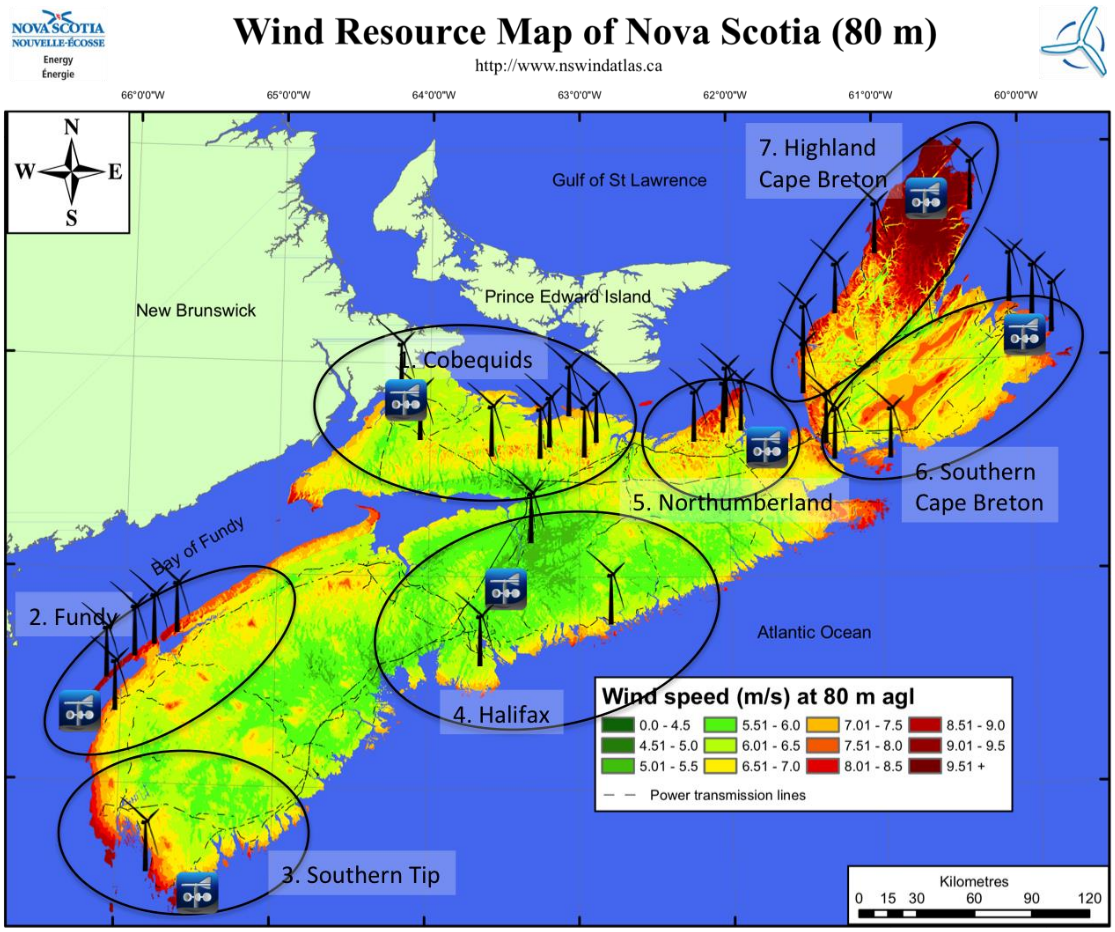

Figure 57: Study area (Nova Scotia), show annual mean wind speed at 80m, and seven regions of WTG development, including the individual wind farms and the Environment Canada weather station location in each region. (From Pearre, Swan 2013b. With permission from ASCE)

In each of the seven regions of WTG development, an Environment Canada weather station was selected to provide a history of weather conditions. A three year wind speed time-series $U_{Hub}(t)$ (for calendar years 2008 through 2010) at WTG development sites was created from Environment Canada weather station data extrapolated from 10m station anemometer elevation to hub height using wind energy development site data, following equation 7:

$$U_{Hub}(t) = \frac{\overline{U}_{Hub}}{\overline{U}_{MET}} * U_{MET}(t) \qquad \text{Eq. 7}$$

In Equation 7, $U_{MET}(t)$ is timeseries data from an Environment Canada weather station, $\overline{U}_{MET}$ is the corresponding average wind speed at that station, and $\overline{U}_{Hub}$ is the reported or calculated mean hub height wind speed at WTG development sites.

This wind speed extrapolation was validated by comparing both the correlation and the relative variability of the appropriate Environment Canada weather station data to commercial wind field data at Spiddle Hill in the Cobequid region. The hourly correlation coefficient between the two timeseries was r = 0.66, which, while not high, is appropriate due to time delays associated with the passage of weather systems between the two locations, separated by roughly 80 km. Aggregated daily and monthly mean wind speed correlations improve (r = 0.83 and r = 0.91, respectively) and account for synoptic-scale and seasonal changes, respectively.

Wind speed timeseries were transformed into WTG power output timeseries by i) making an air density velocity correction following the principles developed for variable pitch turbines by the IEC (IEC 2005), and ii) interpolating wind speeds to power outputs by a power curve transform. The two most popular models of wind turbine in the province are the GE 1.5 SLE and the Enercon E82, which together make up roughly 70% of present WTG capacity. WTG power output was calculated for each region assuming a that each machine type comprised half of installed capacity. An average of the power curves for these two machines was used to transform adjusted hub-height wind speeds into hourly electricity power outputs specific to each region.

10.2.2 Changes in electricity demand

Future electricity demand can be described by the expected annual average demand and a characterization of the variability about that average. The annual average demand in Nova Scotia has exhibited slow and unsteady growth in recent years, however load forecasts filed by with the provincial utility review board project gradually decreasing demand over the period of this study (Nova Scotia Power 2011). These projections may overestimate future demand, as they do not reflect the closure of two pulp and paper mills in 2012 that together constitute about 18% of total provincial load (Nova Scotia power 2012). The projected demand, including the effects of interruptible demand (i.e. industrial users which can switch off upon notice) and the active energy efficiency upgrade programs of Nova Scotia are shown in Figure 58, along with linear extrapolations from ten years of reported demand growth.

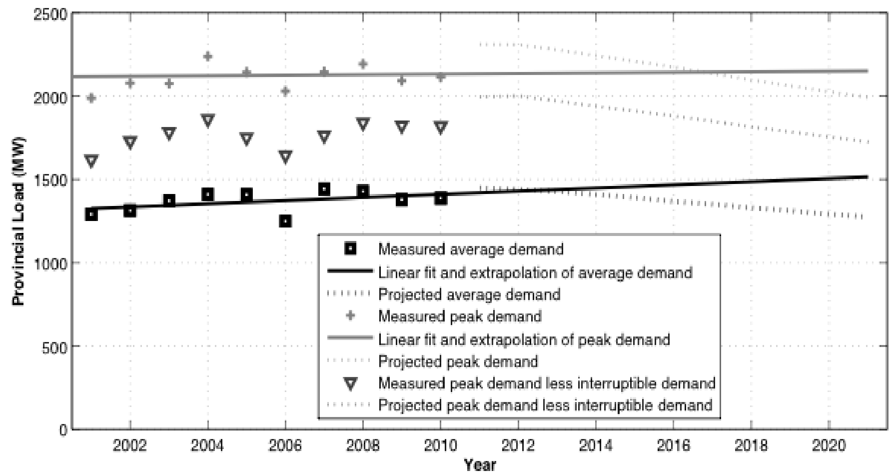

Figure 58: Historic and projected electricity demand values of Nova Scotia. (From Pearre, Swan 2013b. With permission from ASCE).

To characterize the variability of demand, the hourly provincial records for years 2008 – 2010 were compiled. These provincial demand data match the historical weather data both in time span and measurement frequency, so providing a robust dataset for characterizing inter-hour variability[26]. These historical demand data were normalized

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[26]While intra-hour load fluctuations would facilitate an interesting expansion and extension of this research, sub-hourly records are available neither for demand nor for windspeed.

to projected future demand peaks in the regulatory milestone years of 2015 and 2020. Demand peaks were used rather than average demand because peak demands are the extreme case, the greatest test to the system, and the focus of subsequent analysis. It should be noted that active demand side management (DSM), such as smart-grid technologies, and EV charging load shedding, may reduce demand peaks more than the average load changes. However, the load shaping effects of these technologies were not included in this study as the DSM program in Nova Scotia is in its infancy and its effect is difficult to anticipate. The historic distribution of peaks, which included some interruptible load effects, is simply scaled to future projected values following Pearre & Swan (Pearre, Swan 2013a. With permission from ASCE).

The projected provincial demand timeseries is used in the assessment of required WTG capacity to meet regulatory milestones. It is then further used within the energy storage model; the difference between demand and WTG power is the dispatch signal which must be met by conventional generators and energy storage.

10.2.3 Assessment of WTG capacity required at milestone years

Because renewable resources vary year to year, it is reasonable to expect the provincial utility will target higher renewable energy fraction than is required. The Nova Scotia electricity utility exceeded 2011 renewable energy requirements by 6.2% as determined by electricity production (NSUARB 2010b). A value of 7% is used as the design exceedance of regulated renewable energy requirements for all modeling.

10.2.3.1 Current Qualifying Renewable Generation Capacity

Resources qualifying toward renewable energy targets in Nova Scotia are solar, wind, hydroelectric, ocean, biomass, and landfill gas. The WTG capacity to meet upcoming requirements depends on the fraction of generation supplied by each renewable energy sources.

Historically, the majority of renewable electricity in Nova Scotia has come from hydro. While hydroelectric output varies from year to year due to fluctuations in rainfall, the Nova Scotia utility's installed capacity of 399 MW produces an annual average of 114 MW, or 8.2% of provincial average demand (Statistics Canada 2009, Statistics Canada 2003, Statistics Canada 2007, Statistics Canada 2011). Existing biomass and non-utility owned hydroelectric together offer 26 MW of capacity (NPCC 2007). A proposed 60 MW biomass co-generation plant would increase this total to 86 MW (NSUARB 2010a). The new plant will deliver dispatchable power with an annual average capacity factor of 74%, giving a 44.3 MW annual average, or about 3% of provincial average demand. For subsequent calculations, all biomass and non-utility hydro facilities are assumed to operate at the same 74% capacity factor, andto therefore supply on average 63.6 MW. These data are tabulated in Table 12. For the subsequent analysis, it is assumed that the remainder of delivered renewable energy will come from WTG, with the exception of a proposed large-scale hydroelectric project that will roughly double hydroelectric energy supply to Nova Scotia, discussed in more detail in section 10.2.3.3.

10.2.3.2 The Year 2015

The projected average annual provincial demand in year 2015 is 1390 MW (Nova Scotia Power 2011). To meet the 25% renewable electricity requirement with a 7% buffer requires an annual average renewable electricity power of 372 MW.

To produce 372 MW of qualifying renewable energy the present average 287 MW renewable power must be augmented by an average 84.7 MW from new WTG (Statistics Canada 2009, Statistics Canada 2003, Statistics Canada 2007, Statistics Canada 2011, NPCC 2007, NSUARB 2010a). Future wind developments may not be quite as productive as present developments because: i) expanding existing wind farms will subject future WTG to shadow effect, and ii) the best locations (both for farms and for individual turbines) are likely to be the ones that were built on first. To account for these effects, the power output of new WTG installations for 2015 was calculated assuming wind speeds to be consistently 5% lower than those available to existing turbines. The resultant capacity factor of new wind generation, including the effect of 96% availability, is 33.9%. To supply the new average 84.7 MW power, an additional 250 MW (84.7 MW / 0.339) of WTG capacity is required, almost doubling present capacity, as shown in Table 12.

10.2.3.3 Year 2020

For the year 2020 the projected annual average provincial demand falls to 1290 MW. To achieve 40% of this demand, with a 7% exceedance factor requires an average 552 MW power of qualifying renewable energy. This will be achieved through all renewable energy described up to year 2015, along with new qualifying 2020 renewables. A planned development to bring Labrador hydroelectric through Newfoundland, Nova Scotia and on to New Brunswick and New England will include "approximately 165 MW of capacity and about 1000 GWh of energy delivered" annually for Nova Scotia use (ACFE 2011), equating to average 114 MW of power. This resource, while still under review, has a high probability of being built and is thus included in this assessment. To achieve the year 2020 objectives, with wind speed and availability assumptions identical to 2015, an additional 195 MW of WTG capacity is required as shown in Table 12.

Table 12: Existing renewable generating capacities and additional WTG capacity required to meet the renewable electricity milestones for year 2015 (25%) and 2020 (40%). (From Pearre, Swan 2013b. With permission from ASCE)

Resource	Capacity (MW)	Capacity Factor	Average Power (MW)	Portion of 2015 Renewable Electricity	Portion of 2020 Renewable Electricity
Hydro (Existing)	398	28.6%	114.0	31%	21%
Tidal (Existing)	20	19.0%	3.8	1%	1%
Biomass (2012)	86	74.0%	63.6	17%	12%
WTG (2012)	300	35.3%	105.8	28%	19%
New WTG (2015)	**250**	**33.9%**	**84.7**	**23%**	**15%**
New Hydro (2020)	165	69.2%	114.0	-	21%
New WTG (2020)	**195**	**33.9%**	**66.1**	**-**	**12%**
Total	1414			372 MW	552 MW

The values of WTG capacity that must be added for years 2015 and 2020 (bold values in Table 12) will be used to proportionally scale the WTG power output timeseries developed from historical data.

10.3 Energy storage model

The seven regional WTG hourly power output data were weighted by installed WTG capacity and summed to produce the provincial WTG power timeseries. The wind power timeseries is then subtracted from the projected provincial demand for the period to give a required provincial dispatch power. This dispatch power represents the controllable power required at each time step that is supplied by conventional generators (e.g. fossil fuel, hydro) or energy storage. The dispatch power is used as the input to the energy storage model, which is run through twice to evaluate the effect of storage on two distinct objectives. Objective 1 caps conventional peak power by supplanting it with energy storage power output. Objective 2 limits conventional power ramp-rate by using energy storage power output. Ramp rate is defined as the difference in dispatch power between successive hours, and indicates the rate of change of power output required of dispatchable resources. The operation of the model as described in this section is represented in Figure 59.

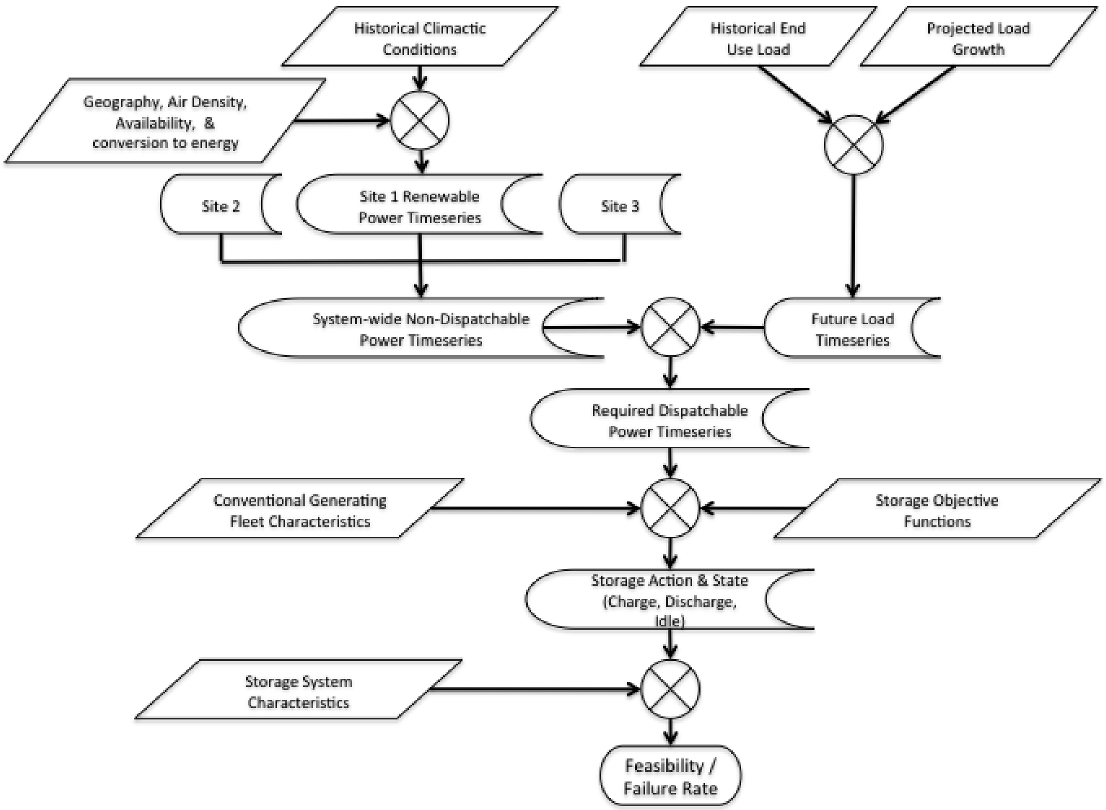

Figure 59: Flow chart of variable renewable energy production, dispatch, and storage model operation. (From Pearre, Swan 2013b. With permission from ASCE)

For the peak-capping objective, power is supplied by the energy storage whenever conventional power exceeds an adjustable threshold. Support by the energy storage is continued either until the storage is depleted or until dispatch demand falls below the conventional power capability. The energy storage is recharged whenever excess conventional power is available. If the energy storage is completely depleted in the course of supplying peak power, a "failure to meet demand" is registered for that hour.

The threshold is indexed at the end of the run (at the end of the three year timeseries) to the next value and the test is repeated.

For the ramp-rate limiting objective, a target energy storage state of charge of 50% is set so that power can be either absorbed or discharged. When the ramp-rate of dispatchable power exceeds an absolute threshold, either a positive or a negative value, the energy storage charges or discharges as needed to reduce the ramp-rate to the threshold. As in the peak-capping model, the energy storage is returned to one-half charge once the dispatch ramp-rate falls below the threshold. If the energy storage is either completed depleted or filled during the course of moderating a ramp event a "failure to meet ramp" is registered.

The output of the energy storage model is the number of failures for each objective as a function of storage capacity and either ramp rate or conventional generation inferred limitations. Because three years of provincial load and wind production data were used, the number of failures were divided by 3 to produce the hours per year that the storage fails to meet its objective. Figures and tables were developed for years 2015 and 2020.

10.4 Results

Wind power does not eliminate the need for dispatchable generation because fluctuations in demand have no correlation to fluctuations in WTG production. At times they match (both generation and demand are high or low), at other times they diverge (one is high when the other is low). These four conditions, which are illustrated in four days worth of data from the model in Figure 60, all appear regularly throughout the analyzed three-year record.

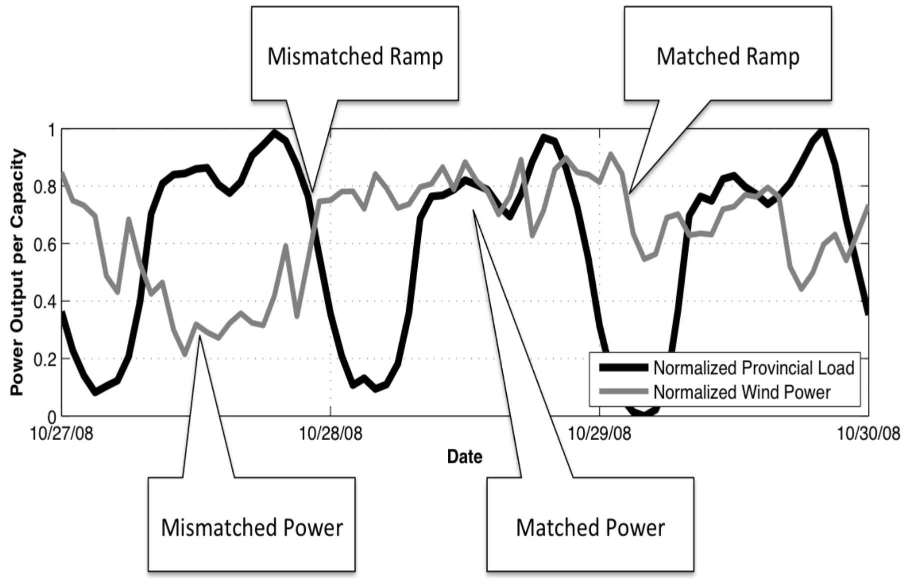

Figure 60: Example timeseries of demand and WTG, illustrating periods of matching and conflicting power, and matching and conflicting ramp. (From Pearre, Swan 2013b. With permission from ASCE).

The future WTG component of the model and electricity demand/WTG-capacity projections are used to evaluate the impact upon peak demand and ramp rates for the years 2015 (25% renewable electricity) and 2020 (40% renewable electricity). Peak demand analysis insures that sufficient output capacity is available at all times to avoid brown/black out. Ramp rate refers to the rate of change of output and is given detailed treatment in the next subsection. The energy storage model is then applied to determine the quantity of storage required to mitigate failures of dispatchable generation to provide for peak demand and ramp rates.

10.4.1 WTG power Effects on Generator Ramp-rates

One important measure of the stability of an electrical system derives from an examination of the rate at which generation output must be varied to match load. Load is generally considered to be an independent variable, which is to say, the demand for electricity varies according to the needs of industry, the effects of weather, and the whims of individual consumers throughout the province. In order to supply this load, dispatchable generating sources must increase or decrease their output. When the rate at which these decreases or increases take place exceeds certain values, matching the changing demand can become a burden.

Just as wind power output can either match or diverge from demand, the changes in wind power output can either match or diverge from the changes in demand. Similarly, just as dispatchable generation must make up the difference between instantaneous demand and wind generation, so those dispatchable resources must also vary their output to provide for these power ramping events. As wind is added to the system, the extreme values of ramp rate increase.

This effect is shown in Figure 61. The black line indicates the frequencies of different rates of change of electrical demand in 2015. The high peak in the middle of the left plot indicates that much of the time the rate of change of provincial demand is in the range of ±150 MW per hour, while the rapid drop to near-zero frequency values beyond ±200 MW per hour indicate that extreme rates of change greater than 200 MW per hour in electrical demand are uncommon. The right plot in Figure 61 shows the same data using a logarithmic ordinate to aid interpretation of low-frequency extreme ramping events. It is interesting to note non-symmetrical behavior of ramp-rate which is a consequence of both climate and human behavior (e.g. turning lights on at similar time in the evening, but turning them off at varying times at night).

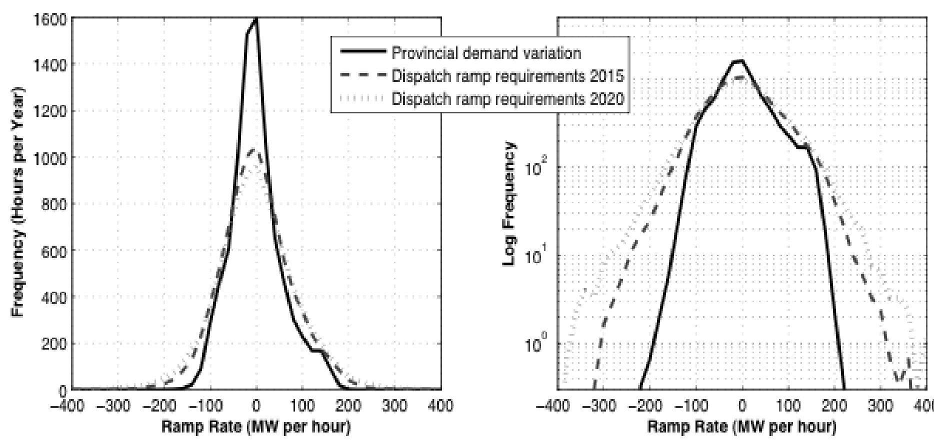

Figure 61: Count of ramp rate occurrence for Nova Scotia demand and modeled dispatchable generation. (From Pearre, Swan 2013b. With permission from ASCE).

In contrast to the conditions that dispatchable generation would have to address in year 2015 in the absence of wind (black line), the dashed and dotted grey lines indicate the effects on dispatch ramp-rate distribution of the projected WTG production for years 2015 (dashes) and 2020 (dots). As expected, by adding uncorrelated variable generation to the system, the frequency of extreme ramp events to which dispatchable generation must respond in increased, while the frequency of stable dispatch conditions (± 50 MW/hour) is reduced.

10.4.2 Energy storage requirements for year 2015; 25% Renewable Energy

In this section, the ability of an energy storage system to supplant dispatchable generation in the renewable energy target year 2015 are described, first as a peak-capping resource, and then as a ramp-limiting resource.

10.4.2.1 Peak Demand Limitation in 2015

If energy storage is tasked to supply peaking power, and thus make possible the decommissioning of existing dispatchable generating equipment, it must be discharged when the difference between load and the non-dispatchable supply of electrical power is greatest. For any given amount of stored energy it is possible for a sustained peak in load to coincide with a sustained lull in the wind, resulting in depletion of the energy storage and undersupply of power, i.e. a failure to meet electricity demand. Both the available dispatchable generation and the quantity of stored energy will affect the number of such failure events. To depict the effects of each variable on the failure rate, a contour plot is presented in Figure 62, where iso-graphic contours follow a constant number of hours of failure per year. These lines are described as “iso-failure lines”. The left and right plots in Figure 62 shows the same data, but with a linear y-axis scale in the left plot, and a logarithmic y-axis scale in the right plot to aid interpretation of the effects of smaller energy storage systems.

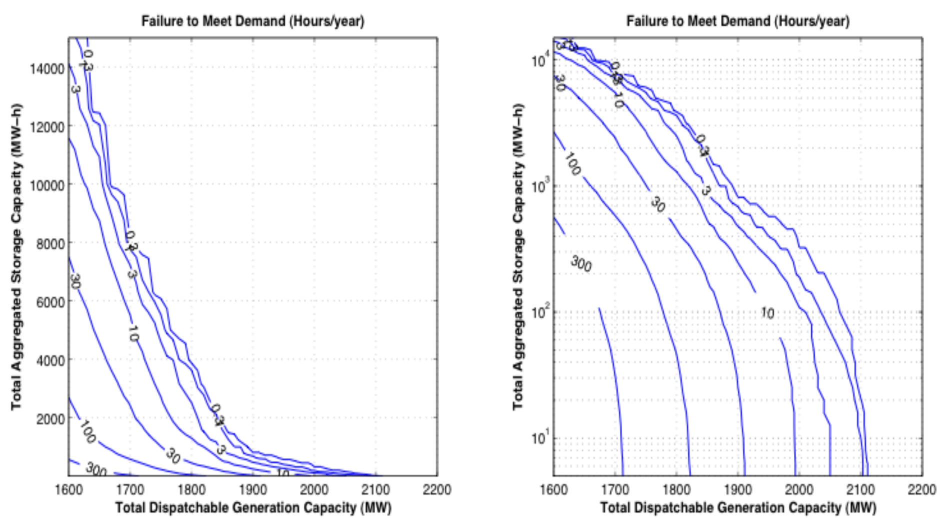

Figure 62: Iso-Failure lines map failure to meet peak demand using energy storage and dispatchable generation in 2015 based on dispatchable generation capacity and storage capacity. (From Pearre, Swan 2013a).

In Figure 62, the x-axis describes the range of peak generating capacities used as indexing thresholds in the energy storage model. The y-axes describe the range of aggregate energy storage. The "iso-failures" contours illustrate the total time in a year during which dispatchable generation and stored energy are insufficient to meat dispatchable load. The maximum predicted peaks in electrical dispatch (demand minus WTG power) in the year 2015 are just over 2100 MW. If 2100 MW of dispatchable generation is available then no energy storage is required (this is where 0.3 hours of iso-failures intersect the x-axis. However, if only 2000 MW of dispatchable generation is available and no stored energy is present, then demand will not be met for approximately 10 hours per year, resulting in brown or blackout (the '10' iso-failure line intersects the x-axis at about 2000 MW, seen most easily on the log plot to the right in Figure 62). If the same 2000 MW of dispatchable generation were supplemented with 400 MW-h of stored energy, then the < 0.3 failure hours/year level of reliability could be retained. (Note that regional reliability (LOLE) requirements under NERC are more commonly 0.1 failures per year. The short-tailed nature of the distribution of frequency of failure suggest, however, that the difference in storage system size between that threshold and the 0.3 per year described here is minimal.)

10.4.2.2 Ramp Rate Limitation in 2015

An alternative objective of energy storage is to limit the rate at which dispatchable generation has to ramp. Figure 61 shows that WTG increases the maximum required ramp rates of dispatchable generation from approximately 200 MW/hour to 400

MW/hour. The iso-failure analysis results of purposing energy storage to limit ramp-rates is depicted in Figure 63. In comparing Figure 63 to Figure 62, note that the y-axis scale describing the energy capacity of the modeled storage system has been significantly expanded to better describe smaller storage systems. The failure contours in Figure 63 represent the number of hours in which the energy storage system is unable to limit ramp events to the maximum rate specified on the x-axis. The relationship was specified as the actual dispatchable generation ramp rate of Nova Scotia is unknown; however, under current grid conditions ramp events are limited to approximately 220 MW per hour.

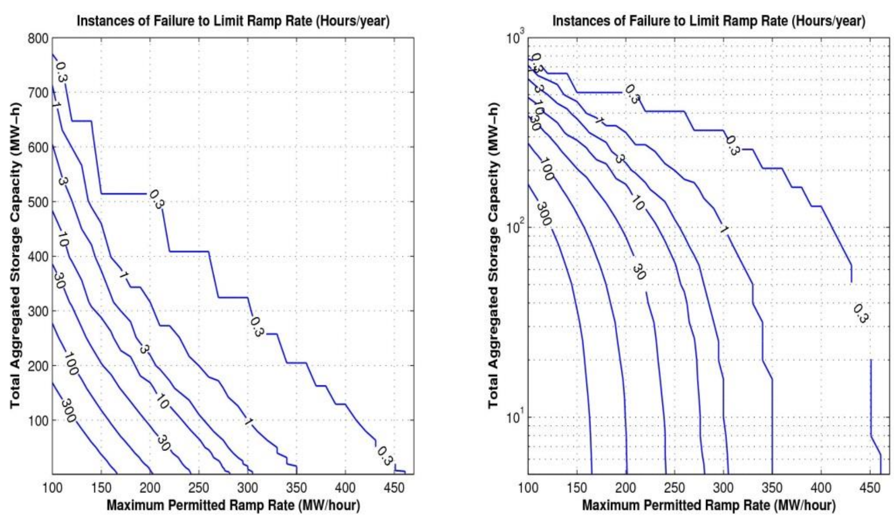

Figure 63: Failure of energy storage to limit dispatchable generation ramp rates of 2015 to a maximum permitted value. (From Pearre, Swan 2013a).

To limit dispatch ramp rates under conditions that this model assumes will be present in 2015 to that of existing demand ramp maxima of 220 MW per hour (shown in Figure 61) would require 500 MWh of energy storage (right plot in Figure 63). However, it is likely that existing dispatchable generation can ramp faster than demand. As such, the required energy storage capacity is likely less.

Note that the one hour timestep used in the model requires the energy storage be capable of providing continuous power for one hour. More specific information about the relationships between the energy and power requirements of the energy storage system is generated by the model, and will be discussed in section 10.4.4. This relationship informs both the suitability of various storage technologies to the task, as well as the suitability of GIVs to such a market.

10.4.3 Energy storage requirements for year 2020; 40% Renewable Energy

In this section, as in 10.4.3, the ability of energy storage systems to supplant dispatchable generation are described. In the renewable energy target year 2020, with 40% of energy coming from renewables, storage system requirements for peak-capping resource, and then for ramp-limiting are assessed.

10.4.3.1 Energy storage requirements for year 2020

The model results for year 2020, analogous to Figure 62 for year 2015, are displayed in both linear and logarithmic scales in Figure 64. Because of predicted efficiency improvements and resulting reductions in total provincial demand (see Figure 58), the iso-failures in year 2020 are shifted to the left (towards lower dispatchable generation) and proportionately compressed compared to those in year 2015, shown in section 10.4.2.1. Peak dispatch requirements are projected to fall from approximately 2100 MW in 2015 to 1925 MW in 2020.

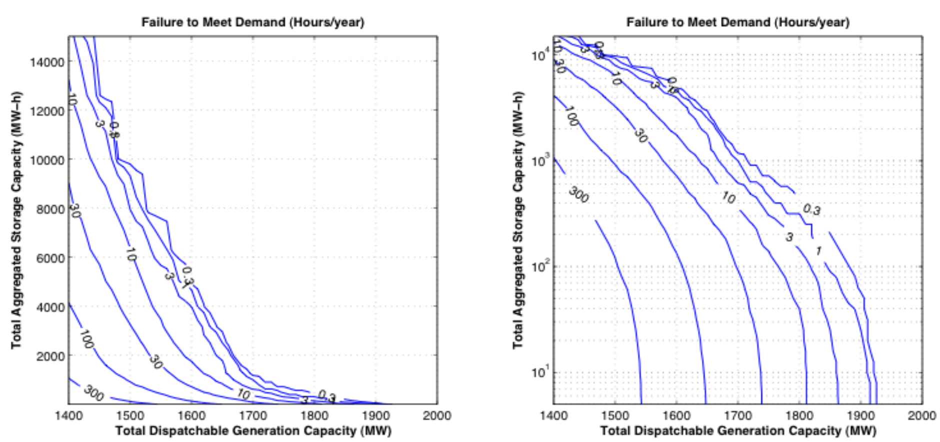

Figure 64: Iso-Failure lines map failure to meet peak demand using energy storage and dispatchable generation in 2020 based on dispatchable generation capacity and storage capacity. (From Pearre, Swan 2013a).

Of particular interest in both Figure 64 and in Figure 62 is a distinct 'kink' in the iso-failure lines. In 2020 this kink appears at about 1700 MW dispatchable generation, while in 2015 Figure 62 it appeared further to the right on the plot, at about 1875 MW generation. (This shift matches the overall shift in dispatchable requirements, and presumably corresponds to the decline in expected peak loads shown in Figure 58).

Individual instances of dispatching stored energy occur when dispatch (total provincial load – WTG generation) exceed dispatchable generation. In successive model runs, the presumed quantity of dispatchable generation is incrementally reduced. The kink occurs where the capacity of dispatchable generation falls below not just the highest hourly dispatch peaks, but below the highest average daily loads. When this happens, the energy storage cannot be fully recharged between demand peaks, so the storage resource must supply multiple peaks in a row. In the two-peaked heating load dominated conditions found in Nova Scotia, these local minima occur between successive evening and morning demand peaks.

10.4.3.2 Ramp Rate Limitation in 2020

While energy requirements for peak capping in 2020 are lower than those for 2015 the increased proportion of WTG capacity (see Table 12) to provincial demand increases the frequency of instances of high ramp-rates. This effect is indicated in Figure 61 by the progressively wider and less peaked distribution curves of ramp-rate. The iso-failures of ramp-rate shift to the right on the plots for the year 2020 given in Figure 65, compared with those found in year 2015, shown in Figure 63.

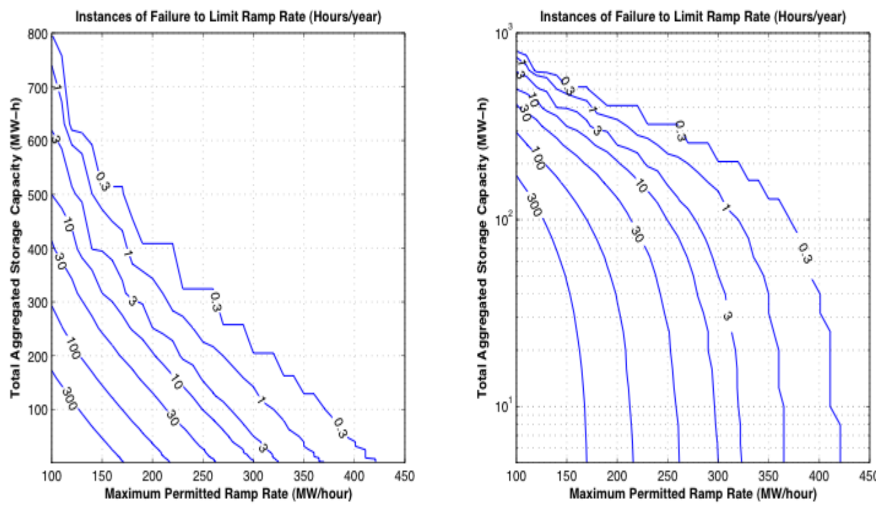

Figure 65: Failure of energy storage to limit dispatchable generation ramp rates of 2020 to a maximum permitted value. (From Pearre, Swan 2013a).

As was the case in 2015, the ramp rate limiting results for the target year 2020, shown in Figure 65, show that significantly less energy storage is needed to manage ramp rates than was needed to manage load peaks. This results suggests that in most cases, any energy storage implementation targeting fossil generation retirement will have more than enough capacity to insure that ramp rates are within acceptable limits. While this potential duel functionality of storage might at first seem like over committing the resource, each function is only called a handful of times each year, so the probability of the two functions coinciding is dramatically lower than either one alone.

10.4.4 System Power Requirements

The results presented in the preceding sections can also shed light on the required charging / discharging rate capacities of energy storage. Because the total load on the electrical system is not changed by the presence of a storage system, the power output requirements of a storage system are equal to the amount of conventional generating power displaced; the same load peaks must be met. By rearranging the data used to produce Figure 64, the storage capacity and power requirements may be compared. Figure 66 shows the minimum necessary energy storage capacity required for various levels of conventional generation displacement while maintaining 0.3 hours of failure per year. The left and right plots of Figure 66 show the same data, by the right plot has been expanded to better show the effects of small storage systems. For both the left and right plots, the left-hand y-axis shows the necessary energy storage system size (in MWh), while the right-hand y-axis shows the necessary operating C-rate to balance power requirements with energy storage.

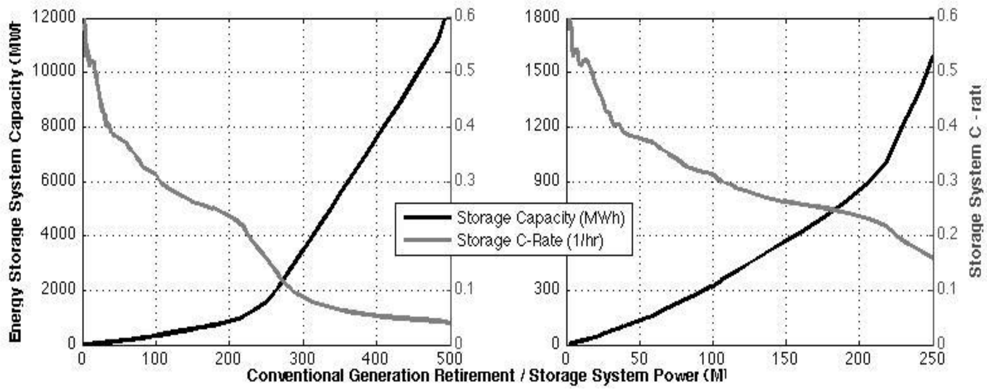

Figure 66: Storage system power requirements to maintain grid reliability (2020 system model). (From Pearre, Swan 2013a).

Progressively more storage energy capacity (shown on the left vertical axis of both plots in Figure 66) is required as more generation power capacity is displaced, but the ratio of those two quantities, energy to power, is not constant. The first 50 MW of generation displacement requires only about 150 MWh of storage, the next 50 MW requires about 200 MWh, the third; about 250 MWh, and the fourth; about 300. At about that point, however, a 'kink' is evident in Figure 66, and significantly more new storage is required to displace each successive MW of generation above about 250 MW. To get from 250 to 300 MW of generation displacement for instance, 900 additional MWh of storage is needed. Though cost evaluation is beyond the scope of this paper, such a kink in the plot may be of interest to policymakers, as it suggests a change in cost-effectiveness.

The ratio of storage system power to energy capacity gives the C-rate (shown on the right axis of each plot in Figure 66), which can be informative as to what energy storage technologies are appropriate (Roberts 2009). The data used in the model are hourly, and consequently the worst-case scenario would be fully charging or discharging the storage in one hour, which gives a maximum possible C-rate requirement of 1. As can be seen in Figure 66, however, required C rates start at about 0.6 and fall with generation displacement. Below the point of the kink (at 200 MW of generation displacement), C-rates of only 0.2 – 0.5 are required. This means that the highest capacity home charging stations, capable of 19 kW of power, would require each GIV to supplying 38 – 76 kWh of energy on the worst peaks of the year. These numbers are not reasonable, and vastly exceed the per-vehicle energy resource shown in Figure 50 for all but the largest battery vehicles, never mind the de-rating of that absolute resource that may be required to insure the car owners' expectations of vehicle service are met. Conversely, assuming 6 kWh of energy are reliably available from each vehicle, a C-rate of 0.5 suggests that an average backfeeding capacity of only 3 kW is sufficient for wind integration, while a C of 0.2 means only 1.2 kW are necessary.

On the other hand, these values are fleet wide (or electrical system-wide) averages, and around the average there will be a distribution. In the context of feeding electricity into the grid from cars, this distribution will take the form of some vehicle owners being willing to send lots of energy back at high power, while others will wish to retain all of their energy for upcoming travel. Because the nature of this distribution rests on the possible responses of vehicle owners to spot market energy prices, it is not revealed in the trip data, it is not possible to estimate the distribution.

10.5 Discussion

The models described in this chapter estimate the impact that likely WTG capacity will have upon peak demand and ramp rate. They also evaluate the potential effects of storage to moderate these effects. The presented figures allow for the identification of energy storage quantities required to mitigate failures to meet demand based on dispatchable generation capacity and capabilities, enabling scenario analysis. An obvious example scenario is one where a coal fired electricity generator is retired by replacing its energy production with that of WTG, and its dispatchability with energy storage. In evaluating this possibility, it should be noted that coal generators are not generally operated as fast ramping load-following generation, so while coal capacity is retired and WTG and storage are added, it is not accurate to consider that wind and storage 'replaced' coal, rather that the combination of reduced total load through efficiency programs, increased electricity supply from WTG, and the load-following ability of storage together make a certain quantity of baseload generation unnecessary.

10.5.1 Retiring a coal-fired electricity generator

The total installed fossil fueled generating capacity in Nova Scotia is currently 1893 MW; a list of these stations and totals of hydro and biomass generating capacity is provided in Table 13. It is evident from Table 13 that coal-fired generators are the major facilities. Of the 398 MW of hydroelectric generating capacity in Nova Scotia, three quarters, or 299 MW, has dispatch capability (NBSO 2005). The 86 MW of biomass and non-utility hydro will also be counted as dispatchable. These resources constitute a total dispatchable generating capacity of 2278 MW.

Table 13: Electricity generators in Nova Scotia (NPCC 2007) with major facility build and expected retirement years (NSUARB 2011). (From Pearre, Swan 2013a).

Facility	Year Built	Turbine Capacities (MW)	Energy source	Expected Retirement
Trenton	1970, 92	150, 157	Coal	2025, 37
Pt. Tupper	1973	154	Coal	2028
Lingan	1980-85	155, 155, 155, 155	Coal	2026-30
Pt. Aconi	1994	171	Coal	2039
Tufts Cove	1966, 73, 77	81, 93, 147	Oil/NG	2020
Tufts Cove (gas turbines)		49, 49	NG	
Burnside		33, 33, 33, 33	Light oil	
Victoria Junction		33, 33	Light oil	
Tusket		24	Light oil	
All Hydro		398	Hydro	
All Biomass		86	Biomass	

To satisfy electricity grid reliability regulations, the utility is required to retain reserve capacity amounting to 20% of the expected firm peak demand (peak minus interruptible demand) (Nova Scotia Power 2011). As this model accounts for the coincidence of renewable electricity generation with demand, the 2020 peak dispatch of 1930 MW is used in the determination of reserve capacity, rather than the peak demand of 2026 MW. This compares favorably to year 2020 projected peak dispatch requirement of 1930 MW when the necessary 745 MW of WTG capacity (the sum of existing, new for 2015, and new for 2020 WTG capacities as indicated in Table 12) are installed.

In 2020 interruptible demand is projected to be 271 MW resulting in a required dispatch capacity, including reserves, of 1991 MW, or 287 MW less than exists today. While this appears acceptable and this amount of generation retirement appears close to the ‘kink’ in Figure 66, it is important to consider the future implications of the coal-fired generators.

As renewable energy in Nova Scotia increases to 40% electricity production in year 2020 the gross energy production of dispatchable generators will decrease. Given that water, the energy source of hydroelectric production, has no cost, this dispatchable energy production decrease will be achieved by lessening the use of coal or natural gas. This will result in a decreased utilization of the thermal electricity generators, and in-effect keeps one or more operating principally to respond to seasonal demand, peak demand and ramp rate. Moreover, Table 13 shows that several coal-fired generators, totaling 614 MW, are scheduled for retirement within 17 years (Nova Scotia Power 2011). Herein lies the issue. As these coal-fired generators are retired the utility must replace their dispatchable capacity or else fail to meet peak demand. It is undesirable to build new coal-fired generation because it commits the utility to decades of purchasing coal. An alternative is the use of energy storage.

As a scenario, the retirement of 614 MW of coal-fired generators may be applied to year 2020. This is reasonable as demand reduction through energy efficiency programs will achieve diminishing returns from years 2020 to 2030. Given this scenario the dispatchable capacity would be 1829 MW (2278 + 165 new hydro – 614). The maximum allowable dispatch demand is calculated by dividing by reserve capacity requirements and adding interruptible demand, giving 1795 MW ((1829 / 1.2 + 271). Figure 64 shows that maintaining dispatch demand in year 2020 below 1795 MW with low risk of failures (< 0.3 hours per year) requires 500 MWh of energy storage.

10.5.2 Size and scale of battery energy storage

Among energy storage technologies, battery energy storage has the characteristics of having moderate energy density, high efficiency, moderate cost, and flexible deployment (Leadbetter, Swan 2012). As an example, this section will examine the implications of a battery energy storage facility of the scale discussed in the preceding analysis (500 MWh). Lead acid batteries are the most mature battery technology and have been deployed in large scale before. Although they have relatively lesser energy storage density, mass is of little concern in stationary applications such as this.

Conventional lead-acid battery technology can be deployed with power electronics and management for approximately US$500/kWh (Leadbetter, Swan 2012), resulting in a cost of $250 million (or $250 per capita in Nova Scotia). The mass of such an installation assuming specific energy of 25 kWh/ton, would be 20,000 tons. The volume, assuming an energy density including the balance of the system of around 25 kWh/m^3, would be approximately 20,000 m^3, which would fit in a space or 50 m x 40 m x 10 m. Meeting peak demand would require considerably less than 100 cycles per year, and therefore the system would most likely be limited by a calendar life of 10-12 years rather than cycle life (GNB 2008, GNB 2002).

It is important to note that such battery energy storage, in conjunction with new hydroelectric generation and ongoing energy efficiency initiatives would enable a high penetration of WTG and allow for the retirement of nearly 50% of Nova Scotia's coal-fired generators by capacity. The deployment flexibility of battery energy storage would allow for strategic placement. As an example they may be placed within the several retired coal-generating facilities which have existing access to the transmission grid. Alternatively they may be placed nearby large scale WTG developments, or as highly distributed storage units located amongst end-users.

10.5.3 Suitability of V2G to Wind Intermittency

In 2010 there were approximately 580,000 registered vehicles in the province of Nova Scotia, of these the vast majority (94%, 540,000 vehicles) were ‘Vehicles weighing less than 4,500 kilograms’ (Statistics Canada 2010), a classification which excludes most commercial trucks and busses, though does include small trucks and the largest personal vehicles. If every single one of these smaller vehicles were a V2G GIV, and each had 10 kWh to supply to the grid through a 10 kW connection, the total resource would be 5,400 MWh of energy, and 5,400 MW of power. From Figure 66, such a resource would be sufficient to permit the retirement of over 300 MW of generation power beyond the quantity needed to meet peak loads. Interestingly, for the function of facilitating wind integration and retiring conventional generation, a 5,400 MWh storage resource would only need a (power) capacity of 350 MW, or 6.5 kW per vehicle.

Clearly, not all vehicles will be V2G capable. At least in the near term, a fleet penetration of even 10% is very ambitious, as the first V2G GIVs are in commercial trials at the University of Delaware as of this writing. At an ambitious 10% penetration, 54,000 V2G vehicles would exist in Nova Scotia. If each had 10 kW of charging / discharging capacity at home only, then according to Figure 2 the instantaneous capacity resource would fluctuate between a nighttime high of about 460 MW and a midday low of about 270 MW (54,000 vehicles * 10 kW each * 85% or 50% fleet fraction at home). According to Figure 49, for vehicles with Nissan Leaf sized 24 kWh batteries, this power capacity would be tied to a fluctuating MSOE resource of between 1010 MWh and 650 MWh (54,000 vehicles * 20 or 12 kWh each), of which the utility might have access to 25% or 162 MWh at the midday minimum. Based on these statistics, for 'reasonable' levels of V2G market penetration and spare energy availability, the energy resource of EVs would be of a size capable of displacing about 50 MW worth of dispatchable generation in Nova Scotia.

10.7 Acknowledgements

The basis of this work appears in print in the Elsevier journal Sustainable Energy Technology and Assessments, and the ASCE Journal of Energy Engineering (Pearre, Swan 2013b, Pearre, Swan 2013a With permission from ASCE). Much credit for the guidance and writing of this paper is due to my coauthor and friend Prof. Lukas Swan at Dalhousie University in Halifax, Nova Scotia. The research was aided and improved by the participation of personnel from the Cumberland Colchester Windfield in the Cobequid Mountains, and a useful and informative review by Michael Samson of Nova Scotia Power Inc.

Chapter 11

IMPLICATIONS, POLICY ANALYSIS AND DISCUSSION

In this, the second last chapter of my dissertation, I will attempt to do three things. First I will briefly recapitulate the major findings of this research, and synthesize the various findings as they apply to the variables under investigation (vehicle range/battery capacity, charging/V2G power, charging infrastructure deployment, and charging algorithm). The second task for this chapter is to identify what entities benefit from each possible change to the system variables. Third and finally, I will suggest mechanisms whereby the beneficiaries may compensate those who must bear the costs of altering or augmenting each variable.

Introducing this chapter requires an acknowledgment that it will be making policy recommendations based on quantitative analysis rather than consumer analysis—however, evidence from previous scholarly work has been presented suggesting that human psychology and consumer behavior factors will be of considerable importance. Wherever possible in the following sections, the policy and design implications of these findings have been formulated in the context of known psychological and social effects, born of my reading of both the literature presented and also of popular media, blogs, and individuals' responses to news stories concerning vehicle electrification. However, there is not yet enough work in the areas of marketing, electric vehicles consumer psychology and behavior for me to feel confident, so some of my policy recommendations I will not be able to state definitively.

This chapter is organized primarily according to the variables used to differentiate model runs. Thus in section 11.1 a discussion of the findings relating to EV range is presented, and policy recommendations are made. In section 11.2, the findings associated with charging/discharging rate and EVSE power are similarly addressed. In section 11.3, the effects of EVSE infrastructure choice are discussed. In section 11.4, findings and consequent policy implications of charging algorithm are presented. While those four sections cover the explicit variables used as model input, an additional section, 11.5, is included to address system interactions and final thoughts.

11.1 Electric Vehicle Range

The first question anyone inquiring about an electric car asks is 'how far will it go?' Single charge driving range has been shown to be a very highly valued factor in the marketability of an EV (Hidrue et. al 2011 found a willingness to pay $5600 to double EV range from 75 to 150), or indeed any plug-in vehicle, and if a vehicle will not sell, it will not be able to provide any transportation or grid services.

11.1.1 Transportation Electrification and Pollution Abatement

There is abundant research, some of it reviewed in earlier chapters, that the electrification of miles otherwise traveled in gasoline power cars reduces total energy consumption, and more dramatically reduces human exposure to pollutants. In addition, this research explored the potential of plug-in vehicles to facilitate the integration into the electrical system of intermittent renewable electricity generation such that greater pollution benefits can be possible not only for transportation, but for all electricity users. When it comes to attributing costs and benefits, it is clear that the benefits of cleaner air obtain for everyone, so paying for this reduction in pollution exposure from general taxpayer funds is entirely appropriate. The attribute that US car purchasers rank highest for EV purchase is range, which provided charging rates at destinations (home, work etc) are over 6 kW or so, is determined mostly by battery size. (The second highest value is fast en-route charging (Hidrue et al, 2011; Table 7), to be discussed subsequently.)

The primary policy driver incentivizing larger vehicle battery size in the United States is a battery capacity dependent federal tax deduction. As currently configured, this deduction is pro-rated by capacity, starts at 5 kWh, and increases linearly in value up to a battery size of 16 kWh, beyond which capacity no additional deduction is offered (Internal Revenue Service 2009a). As the analysis of the population of individual trips showed, the trip length distribution curve is smooth: There is no particular distance where a data-driven vehicle range optimum or inflection point exists, each additional mile of range captures a smaller and smaller fraction of additional trips and therefore abates a smaller and smaller amount of pollution, or pollution exposure.

Beyond about 30 miles of range (8.4 kWh of usable battery capacity, assuming the 280 Wh/mile efficiency assumption used throughout this research), the marginal displacement of gasoline, as well as the corresponding marginal abatement of CO_2 and criteria pollutants, decreases with each additional kWh of battery capacity. An optimal incentive structure to reflect this decreasing marginal benefit to society, and assuming a linear relationship between the capacity to power miles with electricity and the actual displacement of gasoline, would therefore be a decreasing marginal incentive. For example, to reflect the findings of marginal substitutability presented in Figure 3 and examined in Chapters 5 and 6, if $X of tax deduction is appropriate for each of the first 5 kWh of usable battery capacity, then only about $X/8 should be offered for each of the next 5, about $X/16 for the third 5, and only $X/32 for each kWh above 15 kWh. (The exact ratio of travel electrified and pollution abated also depends on charging rate and other variables explored in Chapter 6, so these ratios cannot be precisely representative for all vehicles). A precise dollar value (a value for X) depends on the economic valuation of pollution abatement, which is beyond the scope of this research and would also vary by electrical generating mix.

Secondly, this and other research suggests that the potential to avoid gasoline consumption and emissions of CO_2, as well as human exposure to NOx, SOx, and ozone, associated with plug-in hybrid vehicles (PHEVs) is greater than of pure EVs, as measured on a per-kWh of battery capacity basis. It is certainly the case that the car-buying public accepts PHEVs with far less than 70 miles EV range, while EVs with less than 70 miles of range have failed to find a place in the American marketplace[27].

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27 The Mitsubishi i-MiEV, rated at 63 miles of range, sold just over 1000 units in the US through October 2013, while the Chevrolet Volt PHEV with 38 miles of range

It therefore seems consistent with Pigouvian principles of economic optimization in the face of external costs that a different incentive scales be applied to plug-in hybrids, assuming that the first mile is powered by grid soured electricity. This could be implemented using the same metric (battery energy capacity) is used as the basis of the incentive.

11.1.2 Battery Capacity and Grid Services with Modulated Charging but no V2G

For non-V2G GIVs that provide grid service through modulated charging, the amount of service provided is a function of the amount of travel completed on battery power, and hence the amount of energy space ‘produced. In providing grid support services through modulated charging, therefore, more value is realized by larger batteries, directly related to the benefit in transportation electrification; with larger batteries, more travel will likely be electrified, so more ‘energy space’ will be produced each day.

One of the compelling aspects of modulated charging as a source of grid services is that there is no additional cycling of the battery, thus no appreciable marginal costs to the battery owner compared to simple charging. If grid services that can make use of

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sold almost 19 thousand in the same period. green.autoblog.com/2013/11/05/october-2013-green-car-sales, accessed Nov 8, 2013.

modulated charging resources are procured through an auction at a market clearing price, then modulated charging vehicles would be able to bid ‘zero’ and be price takers, without concern for battery wear. Increasing the pool of resources that can bid zero will drive down the market clearing prices, and lower the total cost of the service by the decreased bid price of the ‘last’ kW.

The effect of marginal battery size on the volume of price-taking bids, however, and thus the appropriate incentive, would be small. Fully evaluating the magnitude of this effect would require the details of resource price curves faced by energy market managers, so cannot be known with certainty. In board terms, however, a marginal kWh of battery size in the fleet increases that vehicles substitutability a small amount, so increases the amount of ‘energy space’ to be filled by a small amount, maybe 0.1 kWh per day, or ~36 kWh per year. With the value of 1 MW-hr of even the most expensive services being measured in tens of dollars, it seems likely that the transaction costs of offering this kind of purchase support would outweigh the benefit of shifting the price curve for dispatchable resources down slightly.

Barriers to a system of modulated charging also include a fixed cost for the communications equipment and system necessary to make plug-in vehicles into GIVs. A small incremental cost will exist on the house/grid side (the EVSE) and depending on configuration, a small incremental cost may exist on the vehicle side. The small size of the resource non-V2G GIVs offer must be compared to the upfront cost of this infrastructure. This cost, like that of marginally larger batteries, could rationally be addressed with upfront financial mechanisms by utilities or other organizations providing grid support. One concern such grid service entities may have is that the mobile nature of vehicles might mean that the capacity they have paid for will be put to service in some other jurisdiction.

For this reason, my recommendation for utilities is to avoid purchase subsidies, but to encourage, though education and rate structures available to EV owners, the development of GIV networks. By building slowly from time-of-use metering and demand response programs, the inclusion and exploitation of charging EVs can be made to inexpensively benefit both utilities and EV owners. Because the electric rate is tied to a location, they may be assured that any service provided will be in their jurisdiction, and because the marginal cost to the vehicle owner of providing the service is close to zero, participation seems likely.

11.1.3 EV Battery Capacity and Grid Services with V2G

For vehicles that can send electricity back to the grid, the benefit of a larger battery depends on the task to which that vehicle's capacity is dedicated. For energy neutral services such as power factor correction and frequency regulation, the size of the battery is unlikely to be of great consequence, though it could be either a positive or a negative: A larger battery will facilitate more travel, so will require more recharging, which will marginally decrease the ability of that vehicle to provide capacity services. On the other hand, for a given control signal and connection power, a larger battery will also experience lower perturbations in state of charge, so will undergo less cycling wear. For energy neutral services, however, both of these effects are minor.

In contrast, for energy consuming services such as spinning reserves, peak shaving or backup for wind/solar energy intermittency, a larger battery greatly increases the grid service value (and marketability of EVs, leading to fleet penetration). Indeed, the potential benefit is likely to increase proportionally faster than the size of the battery. While no direct data on this question exist, research on range buffers[28] by Franke et al. (Franke, Krems 2013) finds that they may either be a fraction of total capacity, or a fixed distance value. If those findings are analogous to energy reserves, then dispatchable energy would increase with battery capacity somewhere between proportionally (such that 1 kWh of marginal battery size affords 1 kWh of marginal dispatchable energy), and as a consistent fraction (such that if the buffer is 25% of the battery (Franke, Krems 2013), 1 kWh would add 0.75 kWh of dispatchable energy).

Attributing the potential benefits of larger batteries in GIVs and V2G vehicles, and thus suggesting a mechanism whereby EV owners can be incented to buy vehicles with larger batteries is less simple. On one hand, the owners of intermittent generation (wind or solar parks) can be said to benefit from the existence of greater stabilizing

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28 Franke's 'range buffer' is the energy vehicle owners prefer not to use while driving, contrasted here with 'energy reserves' owners would not sell back to the grid while the vehicle is parked.

energy storage. Where generating resources are compensated or penalized in proportion to their ability to respond to commands, provide firm capacity, or forecast their output, they are beneficiaries of larger batteries in vehicles. In the absence of structures of that kind, generally in areas without RTO-managed markets, it is the utility itself that is the beneficiary of the existence of increased ESO, so the utility that should be the source of incentive to EV owners. In either case, it is ultimately rate-payers that benefit

If the benefit is to the distribution utilities (DSOs) rather than the TSOs, cost recovery is a bit different. US utilities which are regulated monopolies have guaranteed return on investment, delivered through electric rates (Joskow 1996). Benefits realized by utilities, if paid for by rate recovery, are thus ultimately paid for by rate payers. If an EV storage market is set up efficiently for DSOs, as is being attempted for TSOs (Kempton et al. 2008), the cost of providing service should be lower than traditional means such as distribution system upgrades, redundancy, reserve margins, etc. In an efficient market the cost of second use of additional storage in EV batteries should be lower than the reduction in total electrical system operating costs due to the existence of that storage. In that case, rate payers ultimately would pay less for a stable, reliable electrical system. These scenarios become more likely with lower cycling cost of batteries, low capital costs of communication, and high participation rates by EV owners.

11.1.4 Policy implications and Recommendations

Greater battery capacity in EVs permits greater displacement of fossil fuels for transport, and correspondingly greater abatement of human exposure to pollution. It thus is advantageous to everyone to support travel electrification[29]. Governmental subsidies for larger battery capacity are therefore socially rational. The magnitude of such an incentive should, logically, diminish with marginal battery capacity in proportion to the diminishing average utilization of that additional capacity (or vehicle range), and should exist in separate scales for pure EVs and PHEVs. It should be noted that a more direct method of accounting for the human health costs of burning petroleum for transportation could be incorporated into the price of gasoline, which would make the operation of electric vehicles comparatively less expensive, and similarly into the price of burning coal for electricity, which would make wind and solar electricity relatively less expensive.

More travel electrification by vehicles that can modulate charging to respond to signals from the grid means more of such services are supplied by a price-taking resource. This will bring down the total cost of grid balancing, benefiting ratepayers. It is therefore also rational for grid balancing entities to subsidize marginal EV battery capacity, provided some mechanism (or de-rating factor) can be devised to keep such

[29]With the possible exception of those who live in the vicinity of coal power plants.

resources operating in a given jurisdiction. In contrast to the health effects, the effect on electrical system efficiency should be addressed by system operators.

11.2 Vehicle Charging and V2G Power

Where the first question asked about an electric cars is how far it can go, the second question is invariably "How long does it take to recharge". The value to potential EV-buyers of fast charging was shown to be similar in magnitude to that of longer driving range, at $8500 to drop recharging time for 50 miles of range from 10 hours to 10 minutes (Hidrue et. al 2011). Various manufacturers of vehicles and charging infrastructure have demonstrated the technical competence to recharge PIVs at rates as high as 120 kW (Tesla Motors 2012), but the benefit of marginal charging power depend heavily on the environment in which that charging rate is made available, and the task to which it is set. In this dissertation I has evaluated a range of possible recharging rates, and based on these results various policy recommendations are possible.

11.2.1 Transportation Electrification and Pollution Abatement

When charging at "base locations", either at home or at work, the benefits of higher charging power to vehicle owners is striking and obvious up to a default base location charging rate of about 6 kW. This research has shown that adding charging power up to this threshold is likely to be the most cost effective method of increasing vehicle utility, or travel electrification. The benefits in vehicle substitutability beyond about 7 kW of average charging power are modest, other than for en-route charging, and the relative value becomes very sensitive to the relative prices of battery capacity and household wiring. For the same reasons of pollution abatement and public health mentioned in section 11.1, it is therefore rational for the government to support higher power charging capability, at least up to about 6 kW. Beyond that governmental support for higher 'base station' charging speed is hard to justify as anything other than industry and technology nucleation. In addition to this, the marginal costs of increasing charging power at these moderate power levels are low enough that the administrative costs of attempting to implement such a policy may well be greater than the cost of the subsidy. However, other possible benefits remain for higher power grid connections.

11.2.2 Charging Power and Grid Services; Modulated Charging

For non-V2G GIVs that wish to participate in grid services through modulated charging, the effective average charging rate will of necessity be lower than the maximum possible power transfer. Put another way, the charging power capacity must be higher by a factor of at least two (depending on service) than the average charging rate. In this context, therefore, if a 6 kW average charging power captures most of the EV substitutability, a 12 kW charging capacity permits that EV to participate in grid stability services most of the time while preparing for upcoming travel at that same 6 kW rate.

It is also noteworthy that the value offered to be grid by such vehicles, in cases unconstrained by the need to charge at full power for the next trip, is independent of charging power. The circumstances where it would be advantageous are quite specific: when i) asymmetrical participation is possible (i.e., where participants can bid into a 'down' market separately from an 'up' market), ii) the price in the 'down' market is higher than the price in the 'up' market, and iii) the 'down' market signal capacity factor f is low. In such circumstances vehicles would ideally be able to bid a high power capacity P into the higher valued 'down' market, set a default charging rate to 0, and charge at fP, where fP remains greater than the 6 kW that has been shown to deliver most of the substitutability available for an EV of a given driving range. For typical f values of 0.1, this would require 60 kW 'base' location charging to retain vehicle serviceability via 6 kW average charging, while maximizing market participation.

11.2.3 Charging and V2G Power and Grid Services; V2G

For V2G GIVs, this research has confirmed and quantified the much higher value that higher power grid connections make possible. Where feeding energy from the EVs battery back to the grid is possible and energy-neutral markets exist, the value of an online vehicle increases almost linearly with that power. As was the case in the discussion of battery size in section 11.1, this relationship can be limited by battery energy, which causes the divergence from a linear relationship. Of particular interest, this research has shown that a moderate increase in charging/discharging power capability at a home location has a dramatically greater effect on the value of the V2G service available to electric utilities than installing chargers at any combination of additional parking locations, even charging locations dedicated to, and always available to, that specific vehicle.

The value of higher power for V2G service in energy consuming markets such as valley filling, variable generation integration, or spinning reserves, is modest. The amount of service in such markets of which V2G cars are capable is much more likely to be limited by energy than by power, at least once the 6 kW power threshold recommended for EV substitutability has been reached. In the context of wind backup and storage displacing dispatchable generation, this research has shown that the technical requirements of a storage resource will vary significantly with the amount of generation displaced, but generally rely on being able to supply rated power for at least three hours (C-rates less than 0.33 in Figure 66). While valuable grid services may be performed with less than an hour's stored energy, the removal of non-renewable generating resources from the grid is not among them.

This relationship may be significantly different for areas dominated by a few large variable generation resources (wind farms or PV parks). While not analyzed here, large industrial scale renewable energy installations can vary their output almost as fast as single turbines or PV panels when a weather front moves across them. In such areas, higher energy storage *C*-rates may be of much greater value as contingency reserves. In such cases, higher power grid connections for V2G enabled EVs could be an important component of an optimized system. That, however, is a special case, and not broadly applicable, at least to large, interconnected electrical systems.

11.2.4 Policy implications and Recommendations

Two groups benefit from higher power charging. Owners of any plug-in vehicle benefit from increased vehicle utility for transportation, though this effect diminishes above 7 kW of average charging power for 'base' parking locations. (Higher power beyond 6 kW does increase utility for the infrequent case of en-route stops for the purpose of recharging). As with larger batteries, this increase in substitutability will result in the abatement of human exposure to pollution from transportation. Owners of V2G capable vehicles also benefit from increased opportunity to participate in electrical service markets. (The benefits to owners of non-V2G GIVs are minimal). Thus, in addition to the owners themselves, the procurers of frequency regulation benefit from increased capacity bidding into those markets, and thus reduced procurement costs.

The benefits of higher power home charging are large, and the costs are low, at least up to about 12 kW (in the United States). Because of these two factors, the direct support or subsidy of increased power in the grid connection capacity of V2G vehicles is likely to be unnecessary. As an alternative to direct subsidy, the potential beneficiaries of increased power, the utilities, may realize greater return on investment through education of the car-buying public, partnering with car makers, and the development and distribution of communication and control networks suitable to communication with distributed vehicles.

11.3 Charging Infrastructure

To a degree, the investigations made in this research were guided by the parameters tied to vehicle trips in the Commute Atlanta dataset. As such, the questions of charging infrastructure that can be addressed from this research relate primarily to the three infrastructure scenarios discussed throughout this dissertation. Home only charging, Home and Work charging, and charging at all parking locations where vehicles spend more than 30 minutes are the only options to which an analytical approach was available. Additional analysis showed the dramatic effect of high power en-route charging. This research does not address the psychological effects of EVSE emplacements though several scholarly works documenting its importance have been reviewed. What this data driven model can establish is the specific benefits of general EV charging infrastructure models.

11.3.1 Transportation Electrification and Pollution Abatement

Installing charging infrastructure of moderate power at locations other than the home of each EV owner has surprisingly little effect on vehicle trip success (assuming that people do not change where and how long they stop, in order to charge). Even targeted installations of EVSEs at the work locations (assumed to be the second most parked at location, after a home location) of the general public will only slightly increase EV substitutability. In general, the cost of a second EVSE at a known base parking location could be better spent by increasing the capacities of the vehicle. In certain cases, the lack of diversity in the EV market may mean that upgrading vehicle capabilities by a specific cost increment is not possible. While charging at work is conceptually attractive, therefore, this research suggests that at most such efforts should be undertaken on a case-by-case basis, and perused where a specific individual who is a would-be EV-owner can be shown to benefit. This suggests that any subsidy of at work charging infrastructure should be lower than the installation cost. A much more compelling case to justify the cost of an at-work EVSE may exist where multiple EVs can have guaranteed access for a couple of hours each workday to a shared EVSE. In such a scenario, the benefits of the second EVSE obtain for multiple cars, while the marginal cost is divided among the users.

11.3.2 EVSE Placement and Grid Services

In contrast to vehicle substitutability, the ability of EVs to provide grid services is significantly augmented by having dedicated 'EVSEs' located where cars park for the day. The change in service is not just one of magnitude, but of timing; when cars plug in at work, the size of the resource increases by about 50% during working hours, though little, if at all, at night.

For charge modulating vehicles, the availability of a second charging location marginally increases vehicle utility, so increases the amount of 'energy space' that can be filled. More importantly, the ability to provide modulated load during daytime load peaks is likely to be of great value[30]. This value must be balanced against the increased mid-morning loads that will be imposed by vehicles plugging in at work. Depending on the nature of the market in which the vehicles are participating, the additional charging load may be relatively small in proportion to the additional balancing resource because the size of the balancing markets to which cars at work contribute is far smaller than the energy markets on which they impose additional load. In the situation described in section 11.2.2, the load imposed by car charging would be only fP while offering P to balancing services.

For V2G capable vehicles, the ability to plug in at work is a significant addition to fleet productivity. The context for this discussion, it must be remembered, is that only roughly a third of the fleet will be plugged in at work. For these vehicles, plugging in at work not only increases the total amount of energy neutral service they can provide by roughly 50%, it also makes possible the provision of high value services not available from most homes, such as demand charge avoidance.

The majority of cars, though it is a slim majority, will be parked at home, even during the middle of the day. This fact opens V2G capable vehicles up to the possibility of

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30 Ancillary service prices can either peak when loads peak, due to increased competition for generating resources, or can peak when loads fall, where baseload generators that ramp slowly supply the entirety of required power. The value of mid-day GIV capacity is thus dependent on the market.

energy arbitrage by selling back ‘peaking power’ during the hottest summer afternoons. The amount of energy that vehicle owners will be willing to sell and how much they will wish to keep in reserve has not been determined in this research, but will definitional be a quantity less than (or equal to) the ESO values presented in Chapter 9.

11.3.2 Policy implications and Recommendations

The research presented in this dissertation suggest that the benefits of making a second EVSE available to every PIV at ‘work’ (i.e. at each vehicle’s second most parked-at location) has an effect on potential travel electrification similar to an additional 12 – 18 miles of driving range. In an order-of-magnitude analysis, these two mechanisms of greater travel electrification are similar in cost. As discussed above, however, this analysis cannot account for any psychological effect that greater charger availability will have on PIV marketability.

The current trend for moderate power charger installations is to have them at high-visibility locations, where they will be seen by as many people as possible. While adding moderate power chargers at locations where vehicles are likely to park during the day has some effect on vehicle utility and grid service, this research suggests that moderate power chargers at ‘random’ locations (beginning to populate the ‘chargers everywhere’ infrastructure model used in this research), is misguided from the point of view of system efficiency. Using the metrics of substitution days and travel adaptation, this research found that a network of strategically placed high-power chargers is likely to be more effective at facilitating travel, owner confidence, and thus ultimately EV sales.

Where grid services are possible, be they through modulated charging or from V2G, the added value of EVSEs where vehicles park during the day is proportionately greater than the benefit to travel electrification. The prospect of using 'public' charging stations for time consuming, non-critical personal revenue generation, however, seems at best discourteous to other EV drivers who need to charge, and may be relying on those limited EVSE resources to get home. Thus installing moderate power EVSEs at locations not targeted to a specific vehicle seems hard to justify.

In conclusion, this research suggests that from the point of view of system-wide efficiency, home charging and en-route high-speed charging are the optimal charging infrastructure solution for vehicle substitutability. For the benefit ancillary services or other markets suitable to storage, home charging stations should be capable of as much power as possible (likely 12 – 19 kW in the North American market due to SAE J-1772). Where no such energy markets exist, charging powers of at least 6 kW should be strongly encouraged and facilitated by governments, which benefit from pollution reduction, and by vehicle manufacturers, which benefit from greater marketability. Fast en-route charging should be as fast as possible (subject to limits of battery chemistry, practical charging electronics, and site power), but will likely see infrequent use, at least initially[31]. Therefore the beneficiaries of travel electrification, the EV manufacturers and the government, have an interest in supporting the development of such facilities.

Interestingly, these findings comport very well with the strategy being pursued by Tesla Motors. Tesla, which began selling EVs before the SAE had finished their J-1772 charging standard, opted to design, build and install their own proprietary charging equipment. They likewise began installing DC fast charging infrastructure for their owners before SAE released their level III standard, so made their own (Tesla Motors 2012). This research suggests that, while en-route fast charging stations may provide a powerful psychological boost to EV owners, such facilities will face infrequent usage and therefore a challenging business environment. Tesla has opted to build, own and operate its own 120 kW fast charging stations, and provide electricity to Tesla owners for free (MacKenzie 2013), avoiding not only the problem of making such installations a viable business, but various legal issues associated with the retail sale of electricity. This is a direct means of solving the company's problem of marketing EVs. However, manufacturer-specific charging networks are a poor

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[31] In Washington state, with 5000 registered plug-in vehicles, 34 fast charging stations along Interstate 5 were used 1125 times in September, 2013, or an average of just over once per day, each. www.komonews.com/news/business/Drivers-using-electric-car-charging-stations-230342581.html accessed Nov 9, 2013.

solution to the public infrastructure problem. Tesla has deliberately chosen signage and technical interconnect to limit the use of their infrastructure only to Tesla vehicles, a path that would lead to a great deal of redundancy if a different type of charger were made for every make of EV.

11.4 Charging Algorithms and Vehicle-Grid Interactions

Variations in the charging algorithm have been shown to have dramatic effects on the substitutability of EVs, the loads they impose on the grid, and to a certain degree the timing and amount of grid services they would be able to provide. In the discussion of adding battery energy capacity, increasing charging rate, or additional charging infrastructure, the conclusions are roughly summarized by the principle that more is always better, but may cost too much. For charging algorithms, which are clearly nominal (i.e., non-ordinal) data, this is not the case. Not only are different output parameters affected in different ways by changing the timing or speed of charging, but even establishing a ranking of the effects depends on the specific characteristics of the electrical system to which vehicles attach, including whether it is subject to an afternoon-peaking cooling load or an evening peaking heating load, and what kind of energy or capacity markets exist.

11.4.1 Transportation Electrification and Pollution Abatement

Eleven charging algorithms reflecting 'simple charging', charging based on time-of-use only, charging based on foreknowledge of upcoming travel, and charging based on both timing and upcoming trips were evaluated. Their effects on the ability of plug-in vehicles to deliver transportation services was evaluated, and showed considerable variation in EV substitutability. Significant variations were found in both the 'trip success fraction' metric and the 'adaptation days' metric. Either of these measures suggests that an imprudently designed charging algorithm can hurt the potential of a plug-in vehicle to displace gasoline.

These results, however, may not be fully representative of the interactions between a 'preferred' or default charging algorithm and an intelligent vehicle owner with even imperfect foreknowledge of upcoming trips, since that owner should be assumed to have both on-vehicle and remote override control over-ride of the charging algorithm. Because of this complexity, it is the opinion of the author that the strength of this research lies in descriptions of overall patterns, those which most vehicles will follow most of the time, and aggregated properties of the fleet such as grid load through time. In contrast, results that hinge on a few individual cases of the vehicle being unprepared for the next trip, for instance, are of only moderate value.

In this context, vehicle substitutability should be strongly influenced by a vehicle owner who remained cognizant of the state of charge, even with only imperfect knowledge of upcoming trips. Just a few instances of overriding the default charging behavior would have a significant effect on adaptation days, but very little effect on grid load patterns throughout the day. As such, "vehicle substitutability" in this context could reasonably be interpreted as a measure of necessary attentiveness on the part of the owner, i.e., if a given algorithm increases adaptation days, it means that that algorithm would require the owner to pay more attention to her travel needs and the state of charge of her vehicle, and override the charging algorithm more frequently with a “Charge Now” command. In the age of smart phones replacing not only phone lines, but also wrist watches, navigational aids, and laptops, some moderate degree of owner attentiveness to vehicle state of charge may come at very low cost.

11.4.2 Grid Load Timing

The most significant impact of the charging algorithm are to the fleet average grid load through time. The variability in charging load of a fleet of EVs was evaluated under a variety of different charging conditions and algorithms in Chapter 8. One of the most striking conclusions was the effect that predictive charging algorithms had on the load profile. Charging algorithms designed to have vehicles prepared for upcoming trips ‘just in time’, by either charging at the last minute or by charging at a constant rate between one trip’s termination and the following trips start resulted in grid loading very complimentary to (typical) existing grid loads, putting the greatest fleet charging loads at times of day when system-wide loads are generally at their minimum. Of particular interest was the fact that this load shape was affected very little by variations in a default minimum state of charge, while vehicle substitutability was significantly improved by increasing this reserve range buffer.

Charge timing algorithms looking only at time of day were also very effective in concentrating charging loads into defined ‘off peak’ hours. Two findings of the research regarding charge timing are of particular interest. First, uniformly moderating every vehicle's charging rate to reduce daytime or peak loads is of no value. The average load from each vehicle, even at its peak, is already such a small fraction of maximum charging power that such limitations have almost no effect on aggregate fleet load. Second, staggering or adding some element of randomized offset into each vehicle's definition of the start of 'off peak' is of great importance. Failing to do so will lead to load spikes roughly ten times those resulting from totally unregulated charging, albeit they happen late at night and at a predetermined time. Staggering this load spike within each car by even a few tens of minutes will dramatically lessen the height of this peak.

11.4.3 Policy implications and Recommendations

As a guide for policy, the results of this research related to charging algorithms suggests two things: Electric utilities that are concerned about additional charging load from plug-in vehicles have an interest in the development of travel-predicting software, and in distributing or even paying EV manufacturers and/or owners to implement and use it. In many electrical jurisdictions, this effect may already be addressed by Time-of-Use or Time-of-Day rates. In addition, EV manufacturers should be cognizant of this system benefit and, if they are not already doing so as a selling feature, should incorporate the ability to adjust charge timing into their EVs' energy management systems.

11.5 Synthesis of Conclusions

This research deals with the intersection of transportation and the electrical system. That intersection has several historical components, including electricity consumed for refining gasoline or building roadways, but in the quickly emerging era of non-dispatchable generation from variable renewable energy sources, a third intersection is emerging; the use of distributed storage in the batteries of plug-in vehicles. The findings of the research suggest that EV battery storage will not provide enough energy capacity to accommodate high penetrations of a highly auto-correlated renewable resource such as wind in Nova Scotia, (though diverse and spatially distributed renewable resources would be easier to manage, as demonstrated by Budischak et al. 2013). Nonetheless, numerous energy and capacity markets should be able to make use of V2G, providing value to ratepayers and to vehicle owners.

11.5.1 Electricity Planning and Policy

The principles of spatial diversity for the mitigation of variable generation intermittency is well understood to policy-makers. This understanding has spurred a great deal of interest in the construction and improvement of high capacity, long distance electricity transmission. One instance of this is the American Reinvestment Act funding which has earmarked $4.5 billion of economic stimulus money to electric system upgrades including connecting variable generation energy sources to the grid (Crownover 2009). Another project intended to stimulate variable generation integration and intermittency dilution proposed recently is an underwater HVDC transmission line offshore the Mid-Atlantic states (Wald 2010).

The importance of energy storage and load control is also great, and is increasingly being recognized as a practical and economically feasible alternative to transmission. Recently, the state of California made the first effort at recognizing this dependence when it passed Assembly Bill AB 2514. The bill requires that the California Public Utilities Commission "determine the appropriate targets -- if any -- for energy storage systems, and then require the Big Three utilities to meet those mandates by 2015 and 2020" (Woody 2010).

Much of the development of hydroelectric power resources in America was done without resorting to market mechanisms. Hoover Dam, for instance, was to a large degree a depression era make-work project. In addition to large centralized government funded projects, the development of storage could potentially be encouraged through simple market mechanisms like encouraging real-time pricing, and extending those prices not only to large corporations but to individual consumers. The effect of time-of-day pricing (not the same as real time pricing, but a simple step in the right direction) is already being seen, such as in the widespread adoption of electrical thermal storage (from conversations with Paul Steffes of Steffes Corporation).

Related to these topics, as a result of my research, it is possible to draw conclusions about the efficacy of existing market mechanisms to encourage the integration of storage, including storage in V2G-capable electric vehicles. Where such market mechanisms are inadequate to the task of sector or resource development, other potential incentive policies, operated either by governments for the betterment of their constituents, or by corporations for the betterment of their bottom lines may be possible. Several potential mechanisms exist, including "carve-outs" for capacity of specific technologies, low interest loans to overcome capital costs, direct subsidy, or command and control methods.

11.5.2 Electric Vehicle & Transportation System Policy

The results of this study provide information critical to the design of electric vehicles. Average commute distance information has already informed the design of the GM Volt (Dennis 2010), which in turn appears to have influenced the design of the federal tax credit for plug-in vehicles (Internal Revenue Service 2009b).

The other important aspect of the transportation system relevant to electric vehicles is the emplacement of public charging stations, and the business models under which such installations could operate. While there is a great deal of outcry for EV owners to charge up 'on the go', this and other analysis indicates that the frequency of use of public charging stations will be slow to grow (BMW 2010, Anegawa 2009, Pearre et al. 2011). Furthermore, public charging station installation to date has primarily been low-power, whereas this analysis shows that high power (over 40 kW) is needed for en-route charging to be possible without great inconvenience to EV drivers.

These results suggest that while the demonstrated psychological benefits of public fast charging infrastructure, and the consequent increase in utilization of EVs are significant, any market-based business model for their operation may be very challenging, due to the low value of the product being sold (electricity) coupled with the relative infrequency of demand (IRC 2010). In addition, manufacturer-specific infrastructure such as that being deployed by Tesla, cannot be a long term solution for en-route fast charging due to the inefficiency of effort duplication. Consequently there may be a role for subsidies or possibly even public ownership of public charging infrastructure.

Chapter 12

SIGNIFICANT CONTRIBUTIONS OF THIS WORK

In this, the final chapter of my dissertation, I will gather and summarize the novel findings of this analysis that represent significant contributions to the literature, and important results that should influence the design decisions of EV and EVSE manufacturers and/or those of electric system operators. This is not an exhaustive list of the findings of each chapter, but rather focuses on conclusions that have not been reported elsewhere and are of particular interest. The presentation of these results has been roughly ordered according to the level of grid service sophistication, therefore it begins with conclusions related to 'Simple Charging', and progresses towards observations relevant to grid interactive vehicles, concluding with a brief discussion of additional research possible from the Commute Atlanta vehicle trip data on which was built the travel model I used.

12.1 Effects of Charging Infrastructure

In Chapter 6, I quantified the effects of putting a dedicated EVSE at each EV's workplace, an EVSE to which that vehicle would have guaranteed access whenever it was parked at work. This effect was compared to that of increasing the charging or driving range of the vehicles. The results suggest that increasing vehicle range is likely to offer a better return on the invested dollars in terms of transportation electrification. It was noted, however, that this relationship is sensitive to the per-kWh costs of battery capacity, as well as the cost of installing second chargers for cars, and the potential to spread that cost among multiple vehicles that might share a workplace parking location, while guaranteeing access to all of them. Thus the conclusion was that a general policy of installing workplace chargers is ill-advised, but that in specific cases where multiple vehicles could make use of one charger it likely makes sense.

12.2 High Power En-Route Charging

While general policies of installing moderate power charging at specific locations were found to be unwise, the analysis of fleet average annual energy shortfall resulted in a striking finding regarding the practicality of high speed en-route charging. When high power charging is available for the occasions when daily travel exceeds an EVs single charge range, the power levels of such charging need not be exceptionally high to make completing those trips feasible, if not entirely devoid of waiting. The amount of time EVs would need to spend at en-route charging each year, measured in hours, is indicated in Figure 67, a reprint of Figure 19 from section 7.3 below.

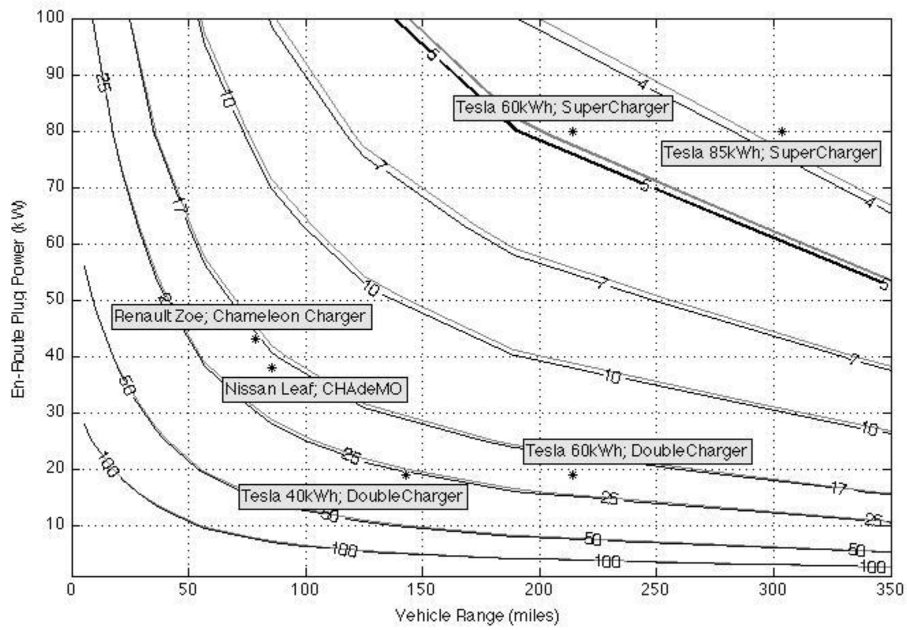

Figure 67: Additional time (hours) at en-route fast charging stations to complete all trips. Vehicles are assumed to have 17 kW (black lines) or 6 kW (grey lines) EVSEs at home only. Liquid fueled vehicles spend about 5 hours per year (highlighted) refueling. Reprint from section 7.3.

Figure 67 assumes moderate power charging at each vehicle's home location, and shows that, for example, on the three or so days when a top-end Tesla Model S would need to recharge en-route, it would need to spend a total of less than 4 hours recharging from an 80 kW SuperCharger. On the 26 days per year when a Nissan Leaf would not complete the required trips, it would spend a total of about 18 hours at a CHAdeMO charger. This analysis assumes that these chargers are available wherever they are needed, which at present they clearly are not, but because the vast majority of charging would take place at home, the required distribution would be significantly less than that of gas stations currently.

12.3 The Hybrid Household Quantified

The potential of electric vehicles to fit into the travel patterns of multi-vehicle households has been a subject of interest for many years. Using this travel dataset, I have been able to evaluate the potential of this mechanism, focusing EV adoption on the two-thirds of US households with more than one car. The results of this analysis are presented below in Table 14, reprinted from section 7.4.

Table 14: Fraction of all households that never require adaption when multi-vehicle households operate as 'hybrid households', for selected example vehicles and charging availability. Reprinted from section 7.4.

Similar To	*Range*	*Charge Power*	Home Only	Home & Work	Everywhere	Intra-House Substitution
	(Miles)	*(kW)*	(Houses %)	(Houses %)	(Houses %)	(Houses %)
Tesla S	*143*	*3.3*	11.2	11.9	22	36.5
Tesla S	*143*	*9.6*	11.4	12.6	25.3	37.9
Tesla S	*143*	*18*	11.7	12.8	25.5	38.2
Tesla S	*306*	*3.3*	31.1	32	48.2	50.4
Tesla S	*306*	*9.6*	32.8	33.4	52.8	51.9
Tesla S	*306*	*18*	33.5	34.2	53.9	52.1
Nissan Leaf	*86*	*3.3*	4.8	4.8	8.1	27.2
Chevy Volt	*37*	*2*	0.4	0.4	1.3	11.8

The results are striking. More than a quarter of all households (not just multi-vehicle households) could use a Nissan Leaf-like EV without ever needing to adjust travel patterns beyond simply taking the non-EV for longer trips, while more than half of households could use a 85 kWh Tesla S-like vehicle (not including the effects of high power en-route charging).

12.4 Charging Load Limits

Numerous scenarios of charging load were evaluated under a 'Charge Right Away' charging algorithm; the highest grid loads seen in the analyses were roughly 1 kW per car. These average loads appeared for a short period of time on workday evenings. It was shown that while several system design changes could be used to reduce the daytime peak loads, no combination of charger size and battery size could drive them significantly above 1 kW per car. These findings can be reviewed in section 8.2 and in Figure 23.

This finding is consistent with most previous research into EV-grid interactions. However, by evaluating a broad range of battery sizes, and in expanding the set of variables under investigation to include both charging rate and charging infrastructure, this 1 kW per car limit has been shown to be relatively insensitive to vehicle design, operation, and infrastructure assumptions. As a result, this conclusion is quite robust, and should ease the concerns of some grid managers.

12.5 Time-of-Use Rate

Peak loads from unconstrained charging were shown to be relatively modest. Nonetheless, the implementation or expansion of simple time-of-use pricing mechanisms to shift EV charging loads from daytime peak hours to nighttime off-peak hours is already appearing. While time-of-use based charging algorithms are simple and familiar to grid managers, not all implementations are effective at removing load from peak times; While reducing daytime charging power seems intuitively to be a rational and convenient response to fears of increasing peak-coincident grid loads, this research has shown that it would have very little effect, since loads would simply accumulate across more vehicles. In addition, all time-of-use charging algorithms that are effective in displacing daytime loads result in a potentially problematic load spike when off-peak hours begins, and every vehicle that was used that day (65% of the fleet or so) begins charging at full rate.

These two potential problems are illustrated in Figure 30 from section 8.6.2, reprinted below as Figure 68. In the upper set of plots, for which charging rates during peak hours were halved, workday peak loads can be seen to reach 0.9 kW per vehicle, only a slight reduction from the 1 kW per car maxima due to unconstrained charging. In the lower plot, daytime loads are significantly reduced by charging only to a 50% battery state of charge, but a load spike reaching as high as 11 kW per vehicle (based on 17 kW charging) results.

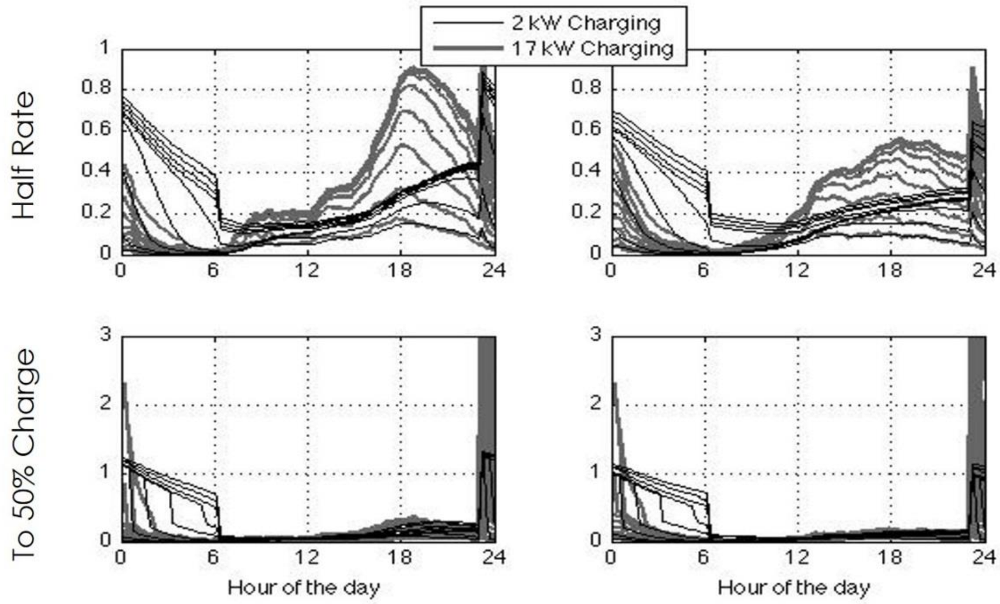

Figure 68: Time-of-Use based charging algorithms; Charge at half rate during day (top plots), and charge to half battery during day (bottom plots). Grid loading for 1.5, 3, 6, 10, 16, 24, 35, 53 and 100 kWh battery sizes on workdays (left) and weekends and holidays (right). Reprinted from section 8.6.2.

12.6 Charging Power Optimum

Perhaps the most surprising results to emerge from this study is that home or work charging at more than 5 – 6 kW will on average only cause minute improvements to the substitutability of an EV. While increasing EVSE power up to about the 5 – 6 kW level causes dramatic decreases in adaptation days, the abruptness of the decline in marginal utility with marginal charging power is striking, as can be seen in Figure 69, a reprint of Figure 14 from section 6.4.1.

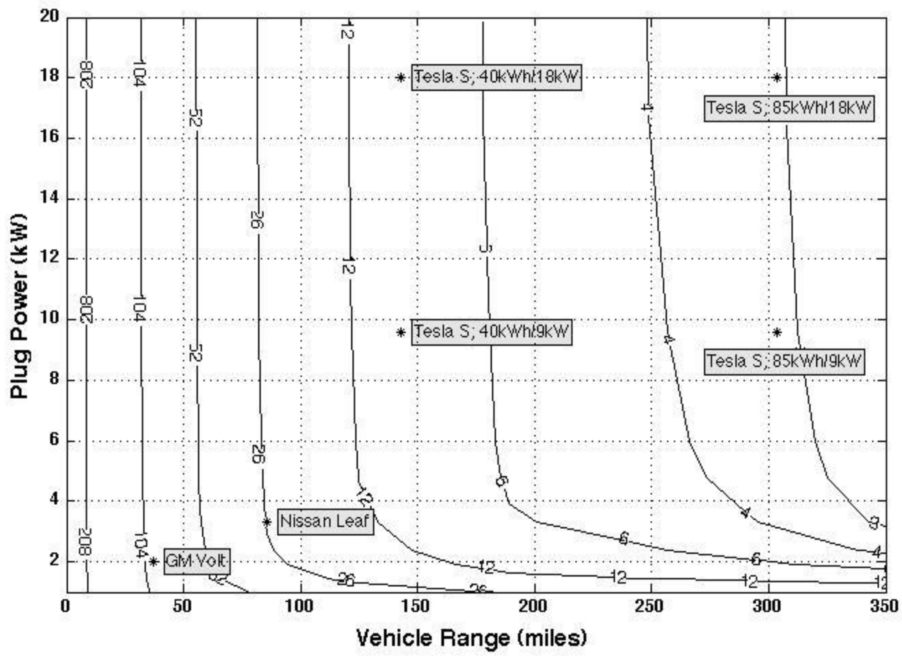

Figure 69: Average Adaptation Days for vehicles charging at Home only. Reprinted from section 6.4.1.

Because of this striking change in marginal utility, it is clear that EVs should at a minimum charge at a rate of 5 – 6 kW. However, that power level refers to average charging power, which is the same as power capacity only for devices that are never expected to supply any symmetrical grid services. There is a great deal of interest within EV research in V2G, and there are enormous benefits to being able to backfeed electricity to the grid, yet many researchers and EV manufacturers express reasonable concerns about the implications of V2G for the cycling wear (and cycling costs) of batteries. In contrast, modulated charging (increasing or decreasing charging load in response to the demands of the grid) carries no such penalty in battery cycles because no battery cycling is added to the cycling already imposed by the vehicle's driving patterns.

While different electrical jurisdictions have different implementation of grid service markets that might be supplied by charge modulating GIVs, the most straightforward response to such a market would be to charge at half of rated power and be able to increase or decrease load to full power or to zero. This scenario suggests that EVSEs and EVs capable of charging at 10 – 12 kW would be able to charge at an average rate of 5 – 6 kW, thus sacrificing very little substitutability, while providing ±5 – 6 kW of grid services almost all of the time.

A power level of 10 – 12 kW also corresponds to what, in many houses in North America, would be a simple EVSE installation; 240 Volts at 42 – 50 Amps. This compares favorably to typical single-family household electrical service of 240 Volts and 150 – 200 Amps, and is also similar to the power demand of a large electric clothes dryer, or electric stove, so is well within the experience of any electrician without recourse to specialist equipment or difficult to source parts.

12.7 A Valuable Data Set with More to Offer

Several other researchers have used GPS-monitored vehicle travel patterns to evaluate the potential of EVs and PHEVs to displace petroleum and to reduce the environmental and human health costs associated with personal transportation. The research presented in the preceding chapters is based on one of the largest such data bases in terms of instrumented cars, and is also the largest in terms of vehicle monitoring period. The potential for expanded research based on these data is great, as the diversity of analytical operations described in this dissertation attest.

Further study that would benefit the field include a refinement of the relative substitutability effects of EVs vs. PHEVs, assessment of the displacement of petroleum fuels directly (rather than through the proxy of adaptation days or trips), and economic analysis of vehicle design, informed by realistic battery cycling and the provision of grid services. In addition, by using vehicle position data directly, which were lost in the development of vehicle trips from time/coordinate pairs, a more refined assessment of the en-route charging model could be undertaken, such that estimates of the number of fast-charging stations could be approximated.

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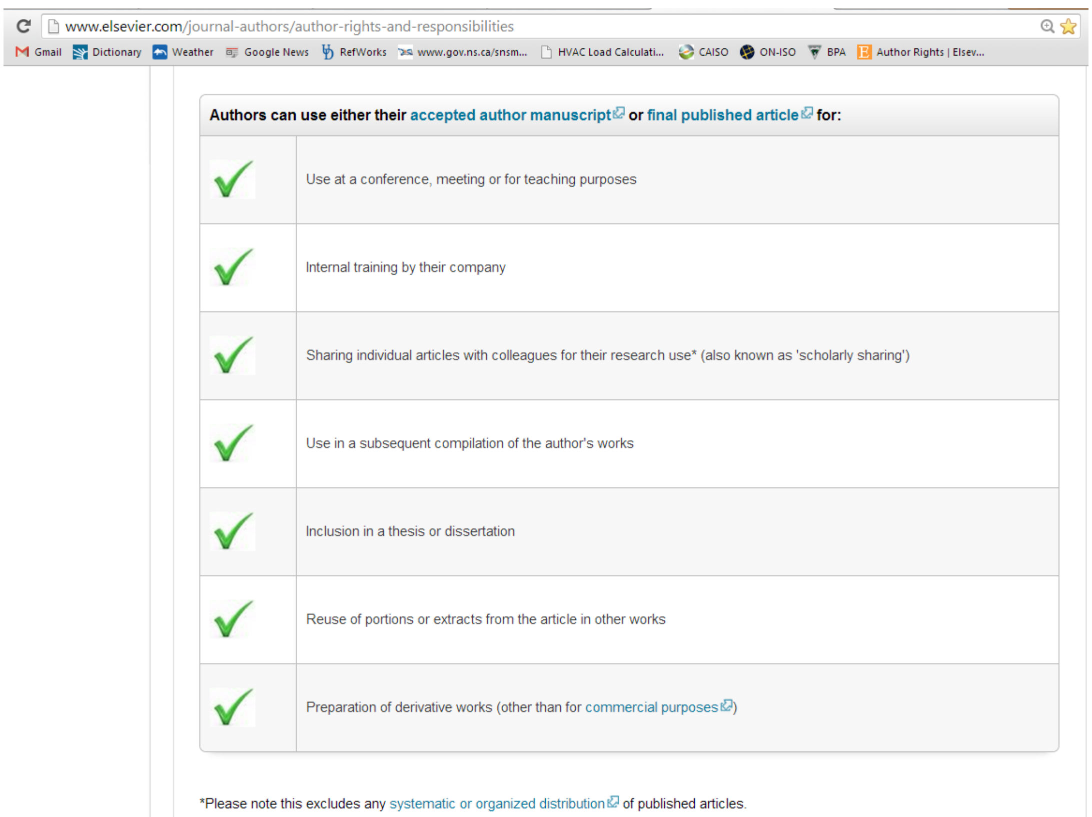

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