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Zero to Sixty Hertz: Electrifying the Transportation Sector and Enhancing the Reliability of the Bulk Power System

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Zero to Sixty Hertz: Electrifying the Transportation Sector and Enhancing the Reliability of the Bulk Power System

by

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Dedication

To my wife, best friend, and muse Caroline, and to our amazing children Caleb, Eliana and Zachary, parents Alan, Liz, Martha & Clif, and grandparents Herb, Lilly, Stanley and Edith. Thank you for sharing me with this work, and for being so supportive and encouraging throughout this long process. Thank you for being a constant source of strength, and encouraging me to always learn and grow.

To my grandma Edith's memory: as a student and teacher of history, she would appreciate the amazing power society has to bring about a brighter future. To my grandma Lilly's memory: she always found ways to bring people together, and would appreciate the new ways people can connect to the world around them. To my grandpa Herb's memory: he would appreciate the ways our economy and energy continue to grow together, and the new opportunities that are coming available to the next generation of students, who will one day become a generation of teachers. To my grandpa Stan's honor: I hope you enjoy the work, and as many times before, see it as an opportunity to make the world a better place, even when it's not easy or requires thinking differently.

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“לֹא עָלֶיךָ הַמְּלָאכָה לִגְמוֹר, וְלֹא אַתָּה בֶן חוֹרִין לִיבָּטֵל מִמֶּנָּה” - “It is not your responsibility to finish the work (of repairing the world), but neither are you free to desist from the work”
- Pirkei Avot, 2:21.

Abstract

Zero to Sixty Hertz: Electrifying the Transportation Sector and Enhancing the Reliability of the Bulk Power System

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The University of Texas at Austin, 2015

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A revolution is underway in the energy sector. Traditional approaches for managing a bulk power system are beginning to give way to a "smart grid" world, in which controllers may have bidirectional communications, with engaged users. At the same time a second transformation has been underway and growing in strength, namely the transition from petroleum as a transportation fuel source towards natural gas for large fleet vehicles, and electricity for consumer vehicles. This thesis focuses primarily on the synergy between the "smart grid" and vehicle electrification transitions.

Moving the transportation sector to electricity as a fuel source, at least in Texas, has a myriad of benefits: Charging an electric vehicle without significant growth in renewable or lower-emitting SOFC technologies leads to very significant (80% per mile, 58% per neighborhood) reductions in CO_2 emissions, as well as significant reductions in NO_X (41% per mile, 17% per neighborhood), PM_{10} (73% / 62%), $PM_{2.5}$ and UFPM (62% / 55%). SO_X levels rose by 37%, but could be mitigated with controlled EV charging strategies.

Vehicle charging strategies also significantly improved the neighborhood's total emissions profile. Adding in distributed energy resources, microgrid generation and intelligent charging, when optimally allocated, can further reduce these emissions. Vehicle charging schemes that respond dynamically to distributed renewable generation can even be thought of as having zero emissions due to the continual balance of PV generation and EV load on the low side of the distribution transformer.

This thesis argues that there may be additionally significant societal benefits by shifting vehicle transportation to electricity, likely far in excess of what could be achieved by controlling power plant emissions alone. Based on an analysis of the ERCOT region, this shift would be expected to produce significant cost reductions for overall energy, improve health (due primarily to the relocation of UFPM far away from major population centers), and lower societal costs. Further gains can be considered as electric vehicles are significantly more energy efficient than their ICE counterparts. Also, on a larger scale, it's generally easier to reduce emissions from hundreds of fixed power plants than millions of moving ICE vehicles.

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CHAPTER 1: INTRODUCTION: MOTIVATION AND SCOPE

In recent years, several different motivations and opinions have started to converge around the electrification of the transportation sector. Electric vehicles (EVs) offer a means to reduce fossil fuel usage in the United States, which corresponds to 30.5% of CO_2 emissions between 1990-2013 (Environmental Protection Agency, 2015). The fossil fuel contributions to electricity generation and thus vehicle charging are primarily domestic, thus transitioning from a perceived imported fuel to a perceived domestically sourced fuel (although this common perception is not entirely accurate). Certainly, though, local energy markets are less connected to international markets than gasoline, and thus less variable.

Adding electric vehicles also allows for greater contribution of intermittent renewable resources into the fuel mix, thus reducing the overall emissions per mile driven. Electric vehicles have, on average, fewer parts at risk of failure, with growing possibilities for non-vehicular uses of its depleted primary cost component, the lithium-ion battery pack. EV prices have significantly dropped in cost from 2011-2015, indicating likely economies of scale, as well as continued innovations and economies of scale around its battery packs (Legatt, 2015).

Since the 2011 release of the mass market Chevrolet Volt and Nissan Leaf, electric vehicle driving patterns, battery degradation, and efficiencies continue to be studied. These vehicles are far more than transportation devices, incorporating cellular connectivity, satellite navigation, and power electronics that could be leveraged to improve, or at least not negatively impact, the bulk and distribution power systems to which the vehicles are connected.

At the same time that electric vehicles are decreasing in cost (along with their primary cost component, the lithium-ion battery), the cost of photovoltaics are also decreasing. These factors have led to a promulgation of distributed energy resources throughout the state of Texas. If one has a goal of decreasing emissions, whether at the global (CO_2) or local (SO_X, $NO_{X,}$, PM_{10}, $PM_{2.5}$, UFPM) levels, it may seem growing levels of wind and solar generation throughout the state would suffice. However, when one takes into account the differences in efficiencies between the internal combustion engine (ICE) and bulk power system, electric vehicle motor, battery and conversion systems (21% vs. 62%; (U.S. Department of Energy, 2011)), shifting transportation to the bulk power system can produce a far more significant reduction in statewide emissions. Of further benefit, this change would shift the emissions that are most harmful to human health farther away from major population centers, and offer both economies of scale and simplified scaled management of overall emissions. Therefore, this paper argues that policies that incentives towards vehicle electrification have a larger positive impact to the public good.

This thesis focuses on an analysis of a simulated neighborhood, considered to be a marginal load within the Northwest Hills area of Austin, Texas. Chapter 2 discusses the backgrounds of vehicle transportation, the ways in which ultrafine particulate matter (UFPM) significantly affects human health, and the theoretical advantages of vehicle electrification, including emissions reductions (including CO_2 and UFPM). It further includes an analysis of several psychological factors that can help to better understand and predict human behavior around transportation decisions. It also analyzes several constraints on the transmission and distribution systems, constraints that could be negatively or positively impacted by electric vehicle adoption, depending on the ways in which the integration occurs. Chapter 3 describes the background and configuration of the neighborhood being analyzed, and chronicles the agent-based simulation software development carried out for this project. Chapter 4 analyzes the outcomes of the research and its implications, and Chapter 5 concludes with an overview of the results and its implications, and the areas of note for future works.

CHAPTER 2: LITERATURE REVIEW

This chapter provides a background analysis of factors at the human level (overall health, behavioral, and neurological), that are impacted or impact transportation. This includes health issues associated with distributed emissions, prior studies analyzing the transition from gasoline to electricity as a light transportation fuel source, psychological factors that impact drivers' decision making, constraints on the transmission and distribution systems, and an overview of several issues that provide challenges in electrifying large portions of the transportation sector, and emerging concerns as the bulk power system becomes more of a "smart grid".

Health issues associated with distributed air quality detractors

VEHICLES

Traditionally, road-based transportation has relied on the internal combustion engine, burning a petroleum variant to power movement. These vehicles typically emit several different classes of molecules, including carbon monoxide (CO), unburned hydrocarbons, oxides of nitrogen (NO_X), partial oxidation products, and particulate matter of varying sizes. Between 50 and 80% of urban air pollution has been attributed to these vehicle-generated emissions. Some emissions, such as carbon monoxide and hydrocarbons, are the primary byproduct of an idling vehicle, while at high speeds or accelerating, other byproducts such as nitrous oxides, with lead (Schneiderman, Cohn, & Paulson, 1970)., or other additives now found in gasoline (Frey, Unal, Rouphail, & Colyar, 2012)) and are the predominant emissions

However, vehicle emissions are also a far more complicated issue, as are the environmental factors associated with the vehicle's manufacture and disposal. Many newer ICE vehicles are tending to outlast their emissions limiting equipment (e.g., engine life vs.

catalytic converter life), leading to a question about the overall lifetime emissions associated with an ICE vehicle.

It is certainly the case that vehicles have grown in their capacity to self-monitor emissions of increasing types and accuracies. However, these technologies rely on the driver as an integral part of the control circuit, in the sense that it is the driver's decision to get the needed vehicle maintenance in response to the "check engine light", should one come on. The driver's decision would therefore affect the emissions output, and often drivers may defer maintenance until the need for the next inspection, potentially until the next legally mandated inspection, or even after if one fails to get the inspection by its deadline. Driving vehicles with expired inspection stickers is a noted issue in law enforcement. For example, 21,000 citations for expired inspections (plus an additional 700 for no inspections) were issued by the Austin police department in 2010 (Austin American Statesman, 2011)

Behaviorally, this means that, aggregated across all high-emitting vehicles, emissions reduction equipment is of concern to society, while to the individual driver the "check engine light" is perceived as a non-immediate concern, and economically likely more affordable in the short term sense to continue, allowing them to continue driving a higher-emitting and less efficient vehicle, rather than paying for the needed work to reduce emissions.

This behavior is also accentuated by the variability among vehicles and the differentials between the "average" vehicle emissions between different areas. For example, one study measuring $PM_{2.5}$ and UFPM emissions from ICE engines found that over 50% of emissions came from 13% of vehicles in a neighborhood with low average socioeconomic status (SES). Emissions vary depending on a variety of host factors, including maintenance and the state of the vehicle, ambient temperature, the quality of the fuel, altitude of the vehicle, and a great many other factors (Minnesota Pollution Control Agency, 2013)

PARTICULATE MATTER

The term “particulate matter” generally serves as a catch-all term for extremely small airborne particles and droplets. Typically, PM consists of a variety of different components, including nitrates, sulfates, organic chemicals, metals, soil, and dust particles. One of the main factors to consider when analyzing PM is its size, as different sizes of PM behave in different fashions. The primary concern from a human health standpoint is around the inhalable particles, including the fine particles (2.5μm to 10μm), and ultrafine particles (<2.5 μm). Both particle types, when they enter the nose, are inhaled into the lungs, and can pass into the blood stream. The ultra-fine particles are sufficiently small as well to traverse the blood-brain barrier, and thus enter the brain and spinal cord, potentially causing damage to the blood-brain barrier and increasing the admittance to subsequent larger particles in the bloodstream.

Particulate matter inhalation has been associated with premature death in people with heart or lung disease, increased risk of cardiac arrest for healthy people, cardiac arrhythmia, and increased risk of asthma exacerbation, decreased lung capacity, and increased difficulty with respiration (EPA). Estimates of mortality due to particulate matter are significant. The World Health Organization estimates 800,000 premature deaths per year due to $PM_{2.5}$, ranking it as the 13^{th} leading cause of worldwide mortality.

Unfortunately, monitoring of particulate matter emissions is rather sparse, both at the vehicle and electric power generation level. For places where emissions are measured, they tend to be far more at the PM_{10} level, rather than the UFPM level, and not as directly linked to power plants as CO_2, SO_X or NO_X sensors. Several source-level methods have been employed to track emissions from coal plants, and are affected by a variety of factors, including combustion temperature, coal type, and presence of scrubbing technology. An analysis using electron microscopy on combusted coal indicated approximately 15% of small-size particle emissions from Montana coal fly ash are less than 2.5µm in diameter, although when larger-size particle are taken into consideration, the percentage of volume drops to near zero. Western Kentucky coal fly ash is somewhat different, at about 3% of volume for small particle size, and near zero overall. This research measured experimentally combusted coal without scrubbing technology, and therefore may not represent real-world output of coal power generation (Chen, et al., 2004). However, if the relationship holds, it would indicate that the proportion of the most harmful particles to human health from electric power generation from coal is fairly low.

It is likely that the chemical composition of the ultrafine particulates are also related to human health, and that further relationships between certain types of heavy metals and other elements have different implications for human health (for example, peeling an orange generates a significant amount of ultrafine particles, however they may be less harmful than equivalently-sized metals). Overall, the transit of external organic and metal particles into the central nervous system ultimately is undesirable, and thus particles are thought of in this paper based on their capacity to transit into the central nervous system, rather than a more detailed analysis of the types.

The particle emissions from vehicles are also highly variable. Analysis of emissions near a London major roadway between 1998 and 2001 indicate that particles > 60 nm in diameter tend to be emitted by heavy-duty (primary diesel-fueled) vehicles, while smaller particles between 30 and 60 nm are primarily emitted by light duty traffic. As wind speed increased, or distance from the roadway grew, the overall particle counts reduced significantly, in an inverse-square distribution. However, the smallest particles, between

11 and 30 nm in size, tended to be moved less by wind, and also showed an inverse association with temperature, peaking in the early morning (Charron & Harrison, 2003).

Overall, a great many significant relationships between particulate matter exposure and human health have been noted. These included increased pediatric emergency room visits, type II diabetes, obesity, hypertension, depression and anxiety even when accounting for socioeconomic status, sex, age, tobacco use, education, BMI and occupational exposure e.g., (Pearson, Bachireedy, Shyamprasad, Goldfine, & Brownstein, 2010).

SMOG

Simplifying a very complex series of interactions, smog is formed through the combination of emissions and sunlight. There are a great many studied interactions between smog and human health. For example, a person who has already had a heart attack is three times more likely to have a subsequent one on a high-smog day, as compared to a low-smog day. Similarly, patients with implanted cardioverter defibrillators had roughly an 80% increase in probability of a defibrillation event two days after a high smog day (Peters, et al., 2000).

One of the most significant high-smog days recorded was on January 12 2013, in Bejing. There, the Air Quality Index (AQI; measured by ozone, O_3 + fine particulate matter, $PM_{2.5}$) was at a level of 755, well in excess of the formerly theorized limit of 500 when the EPA generated the index. PM2.5 was measured at 886 $\mu g/M^3$. The event was described as, "… all of Bejing looked like an airport smokers' lounge." This had the effect of reducing visibility to less than 50 meters. (Wong, 2013).

Based on hospital intake records, this high AQI event corresponded to a 16% increase in emergency room visits, 12% increase in outpatient visits, and 69% increase in hospital admissions. As the event ended, there was a heavy decline in these factors, as was also noted in London's severe 1952 smog event. When analyzing hospital records against air quality metrics in Bejing between December 2012 and January 2013, each 10 $\mu g/M^3$ increase in PM_{10} was associated with a 1% increase in ER visits, 0.7% in outpatient visits, and a 3.9% increase in hospital admissions (Chen, Zhao, & Kan, 2013). Another analysis on particulate inhalation in China concluded a linkage of roughly a three-year life expectancy reduction for every 100 $\mu g/M^3$ average daily air particulate levels. When scaling this number to the Chinese population, the authors conclude an aggregate loss of 2.5 billion years of aggregate life expectancy for its 500 million residents, due to cardiopulmonary disease (Chen, Ebenstein, Greenstone, & Li, 2013).

Bridge Apartments Study

One of the early long-term health psychology studies was conducted on residents of Brown and Guenther's 1963 Bridge Apartments complex, over Interstate 95 in New York City, adjacent to the George Washington Bridge. Between 1974 and 1991, over 8,000 residents were followed and studied for health, air quality, and neuropsychological function measures, across the apartment's 32 floors.

As early as 1973, children participating in the study were noted to have significant impairments in auditory discrimination (ability to determine a signal sound from noise) and delayed reading skill, for children living on the lower floors, as compared to children living on the upper floors. Initially, this effect was attributed to simple noise levels (Cohen, Glass, & Singer, 1973). Over time, additional analyses indicated that while noise was a major factor at lower levels, additional factors such as higher carbon monoxide and PM_{10} levels were far more dangerous. For example, CO was measured peaking at 22 ppm on the third floor, averaging 14 ppm throughout the day. Unlike the noise factors, CO levels were not significantly reduced at the 30th floor. Other factors, such as particulate counts, were noted to significantly decrease at higher floors.

Studies across multiple apartment complexes have found significant relationships between proximity to major roadways and indoor PM_{10} and CO levels. These values are confounded by tobacco use and other emissions generation (e.g., balcony barbeques), but generally trend to significant decreases in PM_{10} levels at higher floors, with roughly similar CO levels throughout the buildings. Interestingly, there are also seasonal factors, with peak levels measured both in summer and winter, potentially due to increased heating or air conditioner use by drivers nearby the homes (Jo & Lee, 2006).

Given these factors, two interesting conclusions could be drawn. First, given roughly similar CO levels across floors but differing particulate counts, the delayed reading time, shorter life expectancies and other factors are likely related to the higher particulate counts. Second, that there may be an aggregate compounding effect in high smog situations, namely that vehicle drivers are likely to spend more time with their windows up running climate control systems, and thus increasing vehicle emissions and therefore contributing in greater proportion to smog.

Figure 1: A view of the Bridge Apartments, George Washington Bridge, and Interstate 95 in New York City (jag9889)

Mexico City Study

Much of the history and importance of poor air quality have been learned through studies in Mexico City over time. While on the uptrend now, air quality was so poor prior to 1992 that children, when asked to draw a picture with the sky then, tended to use green or yellow crayons instead of blue. Even back in the 1940s, air quality was sufficiently poor to obscure visibility to a mile or less, often occluding the snow-capped mountains. Particulate matter was traced back to a variety of sources, including industrial manufacture, electric power generation, and sewage being pumped into open air areas. It is one of the few places in the world that diseases that are typically fluid-borne (e.g., hepatitis, dysentery) can be inhaled (Western Hemisphere, n.d.).

Studies on both children and dogs living in Mexico City showed several signs of neurological trauma, including increased neuroinflammation, amyloid plaques, and neurofibrillary tangles. For example, 56.5% of the children studied showed white matter lesions in the prefrontal cortex, as compared to 7.6% of controls in a nearby town. The dogs showed a similar rate of neurological trauma (57%), and dog autopsy studies indicated the presence of ultrafine particulate matter (UFPM) in their brains, comprised of equivalent particle types to airborne ultrafine particulates. These studies are particularly alarming for human health, as the prefrontal cortex is responsible for higher-order and abstract reasoning, and thus a key structure used by members of a society striving to improve complex situations such as this one. Children followed who moved to Mexico City showed growing brain injury on MRI, corresponding to equivalent decreases in IQ, particularly in areas associated with frontal lobe injury (Calderón-Garcidueñas, et al., 2012).

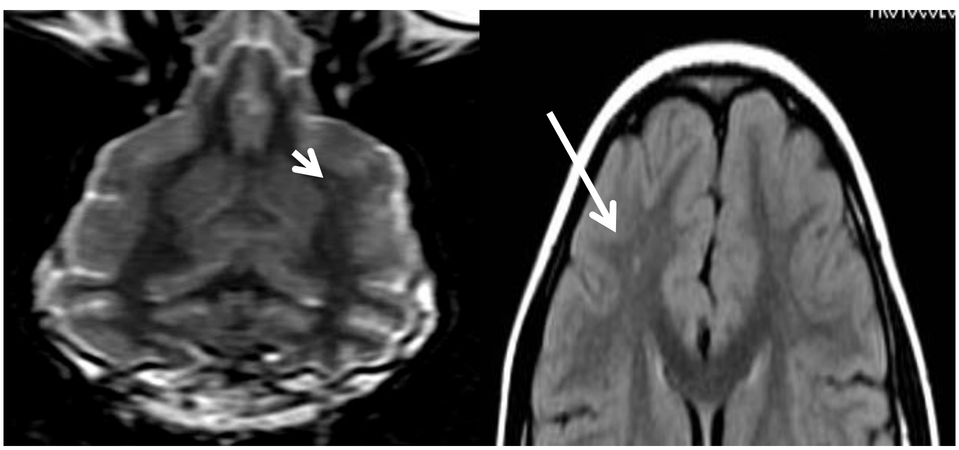

Figure 2: Dog (left) and human (right) MRI studies showing white matter hyperintense legions and neuroinflammation in Mexico City participants

In addition to the prefrontal cortex, ongoing studies have shown ultrafine particulate matter in the olfactory bulbs, hippocampus, and brainstem. Overall, this has led to a loss of > 10 IQ points, failure to recognize several smells (particularly soap), and a significant increase in risk factors for Alzheimer’s disease (Calderón-Garcidueñas, et al., 2015).

PARTICULATE MATTER AND ELECTRIC POWER GENERATION

In June 2011, CPS Energy announced that the coal plant located at the J.T. Deely Station would be shutting down. This plant, having run since the early 1970s, was the first publicly-announced coal power plant to be slated for retirement. In the past several years, many studies have cited the issues associated with electric power generation emissions, including CO_2, SO_2, NO_X, PM_{10}, $PM_{2.5}$, and UFPM. In the final report on the clean air act in 2011, the EPA states that the benefits of the clean air act “exceed its cost by a wider margin, making the CAAA a very good investment for the nation”, citing effectiveness of over $2.0 trillion by 2020, due to reductions in mortality and injuries associated with those emissions.

Avoided Health Impacts (PM2.5 & Ozone Only)*	Pollutants	Year 2010	Year 2020	Estimated Cumulative Benefits 2010-2020 (NRDC)**
PM 2.5 Adult Mortality	PM	160,000	230,000	2,145,000
PM 2.5 Infant Mortality	PM	230	280	2,805
Ozone Mortality	Ozone	4,300	7,100	62,700
Chronic Bronchitis	PM	54,000	75,000	709,500
Acute Bronchitis	PM	130,000	180,000	1,705,000
Acute Myocardial Infarction	PM	130,000	200,000	1,815,000
Asthma Exacerbation	PM	1,700,000	2,400,000	22,550,000
Hospital Admissions	PM, Ozone	86,000	135,000	1,215,500
Emergency Room Visits	PM, Ozone	86,000	120,000	1,133,000
Restricted Activity Days	PM, Ozone	84,000,000	110,000,000	1,067,000,000
School Loss Days	Ozone	3,200,000	5,400,000	47,300,000
Lost Work Days	PM	13,000,000	17,000,000	165,000,000

*Chart from Environmental Protection Agency. The Benefits and Costs of the Clean Air Act from 1990 to 2020, Summary Report. March 2011. p. 14.

**To estimate the cumulative life savings and health benefits of the 1990 amendments from 2010 to 2020. NRDC assumeda roughly linear growth rate to interpolate benefit estimates between EPA's estimates for years 2010 and 2020 and then aggregated the annual estimates across the period.

Figure 3: Avoided health impacts due to emissions, including particulate matter

Interestingly, the EPA study cites the primary reductions in health impacts due to reduction in electric power generation related production of NO_X and SO_2', while reductions to particulates are ascribed to local area sources such as tilling, dry cleaners, open burning, and wild fires, as well as other industrial combustion sources not associated with electric power generation. Improvements on the vehicle side were seen to occur in NO_X reductions, as well as VOCs and carbon monoxide. (U.S. Environmental Protection Agency Office of Air and Radiation, 2011)

Vehicle Electrification – moving transportation to the grid

AUSTIN ENERGY STUDY

Austin Energy owns a large fleet of vehicles, including non-hybrid ICE vehicles, parallel hybrid vehicles, and some early converted Prius vehicles that were capable of running in electric-only mode. In 2009, Austin Energy analyzed tailpipe emissions from their existing gasoline-only fleet vehicles, as compared to the emissions from their fossil-fuel generation fleet. Based on analysis of their driving patterns and emissions, transitioning emissions from the tailpipe to smokestack yielded a 95% reduction in NO_X, and 54% reduction in CO_2. This early research indicated a strong potential overall improvement to society in transitioning to electricity as a fuel source (Alford, 2010). However, these studies did not look at the myriad complex factors associated with energy demand, such as the time of day when the charging occurred and state of power flow on the system (and thus what plants contributed to that vehicle charging, along with its associated emissions).

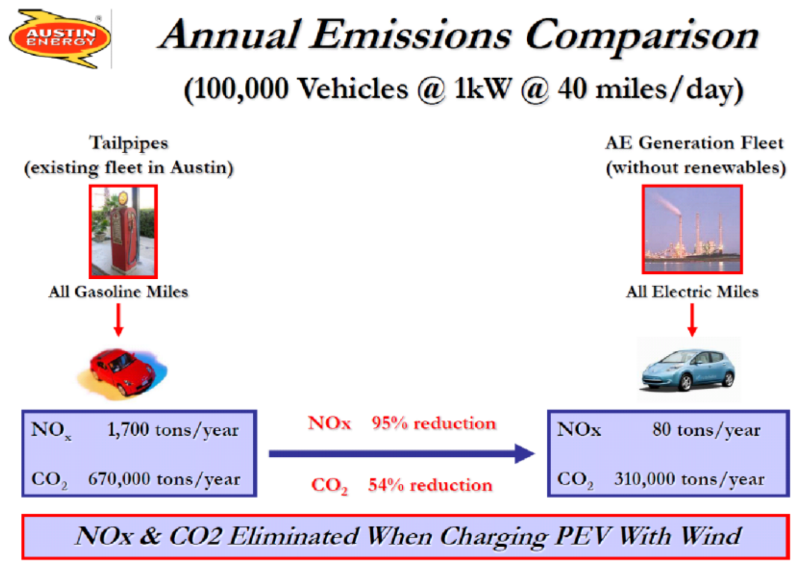

Figure 4: Austin Energy emissions comparison between tailpipe and smokestack

MEEHAN STUDY

Previous research at University of Texas at Austin also looked at the emissions implications of vehicle electrification. These analyses included multiple scenarios looking at various charging patterns for both the Chevrolet Volt and Nissan Leaf. The research further highlighted the emissions reductions due to renewable generation, despite leading to slight increases in fossil fuel plant emissions due to ramping. Overall, the models indicate vehicle electrification leads to significant reductions in CO_2 emissions, a trend that holds until ICE vehicles achieve an efficiency of around 58 ± 8.3 mpg. According to the model, the cross-over point for NO_X is around 39 ± 9.5 mpg, while SO_2 emissions favor ICE vehicles generally at 0.6 ± 0.4 mpg, indicating a societal cost for SO_2. However, when taken in balance, from both public health and climate change concerns, the reductions in CO_2 are likely more valuable to society than the marginal increases in SO_2 emissions. For example, a recent analysis on the health impacts associated with coal plant emissions indicated a cost to society of \$0.214/kWh due to CO_2 emissions, and \$0.012/kWh for SO_2 emissions. (Johnson & Hope, 2012)

The research further noted that the generation that would serve vehicle charging would be primarily served by combined cycle natural gas units, and then coal units. The increased generation of the coal units was identified as the primary cause of increased SO_2 emissions (Meehan, 2013). However, considering that in 2014, the Government Accountability Office (GAO) significantly increased its 2012 estimates of the number of coal plants that would have retired by 2025, with the expectation that the bulk of retirements will occur in 2015, it is possible that in a few years' time, the SO_2 impact would be reduced by changes in the generation fleet (US Government Accountability Office, 2015).

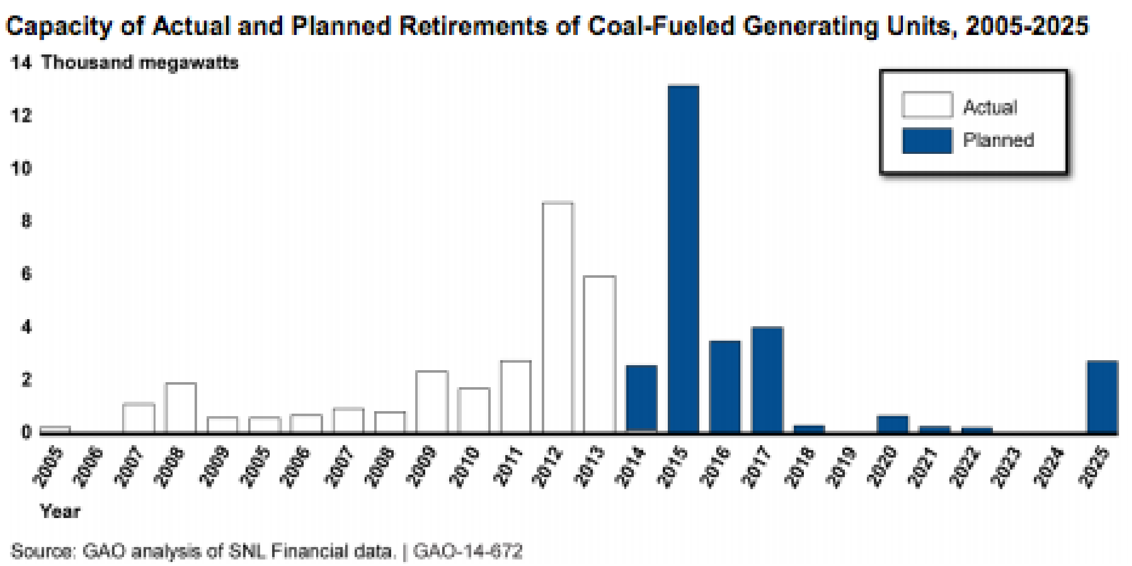

Figure 5: Anticipated coal-powered unit retirements 2014-2025

ECONOMICS OF ENERGY AND POVERTY

Just as tailpipe emissions are not evenly distributed across vehicles, so are energy costs varied across the population. One can imagine a scenario between two energy consumers in Austin.

One individual is of a high socioeconomic status. This individual lives in a home they own, a factor that increases the probability of building or enhancing the energy efficiency of their home. In fact, if that individual were to choose to add rooftop PV and get subsidized by the city, an energy efficiency audit would have to indicate a certain level of efficiency before the subsidies would be allowed to take effect. This individual also owns an electric vehicle, and pays somewhere in the \$0.02 - \$0.04 per mile range, given a flat rate of \$0.11 / kWh, rooftop solar decreasing their overall bill, and a vehicle efficiency of roughly 35 kWh per 100 miles. Overall, this individual has a highly energy efficient home and vehicle, and PV reducing the cost per kWh of energy overall. Given they drive an electric vehicle, their cost per mile is low and relatively stable, given the flat rate of electricity. They are able to afford the high upfront cost of the electric vehicle, and lock in low and stable per-mile costs due to the nature of electricity and its costs.

Take the second individual, and imagine them living at a lower socioeconomic status. They live in a multifamily housing area, and pay rent every month. The landlord, the owner of the building, has less of an economic incentive to audit or improve the energy efficiency of the building, as the renter is paying the utility bill, so the landlord has little way to recover the cost associated with the efficiency improvements. Therefore, the apartment is highly leaky, with poor ceiling and wall insulation, and thus requires higher energy costs to maintain the interior temperature. There are no PV panels on the roof of the apartment, or if there are, the moneys associated with the generation flow to the landlord, not to the tenant. While one could theoretically expect a reduction in expenditures to flow down to the tenant, a high probability of the tenant moving in the near-term future makes such flowbacks to be less likely.

From the transportation energy perspective, this individual is paying a much higher and variable energy cost. Over the past 11 years, gasoline prices in Austin have been highly variable, peaking at $3.97/gallon for 87-octane gasoline in mid-2008, with a minimum of $1.44/gallon at the end of 2008. At the time of this writing, fuel costs are averaging roughly $2.20/gallon. (GasBuddy.com, n.d.) The vehicle driven by this individual is likely to be far less energy efficient. This individual may have purchased a used car to save costs, and while the sticker at the time of the vehicle's original purchase may display an overall MPG of 20 MPG, long-term vehicle maintenance, both by the original owner and this individual may be deferred or outright avoided, and ageing climate control and other systems leading to increased inefficiencies. With these presumptions, one can conclude that at peak gasoline prices, with a low efficiency rating (10 mpg), one could pay up to $0.40 / mile, while at the minimum gasoline prices and high efficiency rating (20 mpg), one could pay a cost of $0.07 / mile, all well above the costs of charging an electric vehicle.

Given the understanding that tailpipe emissions also are significant detractors of local air quality, one must also consider the overall emissions from the tailpipe of the ICE vehicle. When this individual's "check engine light" comes on, the probability that the vehicle will be taken for immediate maintenance may be lower, due to greater financial concerns on their part. As the issue with their vehicle might be associated with increased particulate matter emissions from the tailpipe, it is therefore expected that a vehicle driven by someone in this situation could also account significantly for increases in local AQI and the health of the individual and their neighbors.

Combining both the transportation and home energy costs, the individual at a lower socioeconomic status could be expected to pay higher energy costs per square foot or per person, both on average and in variability.

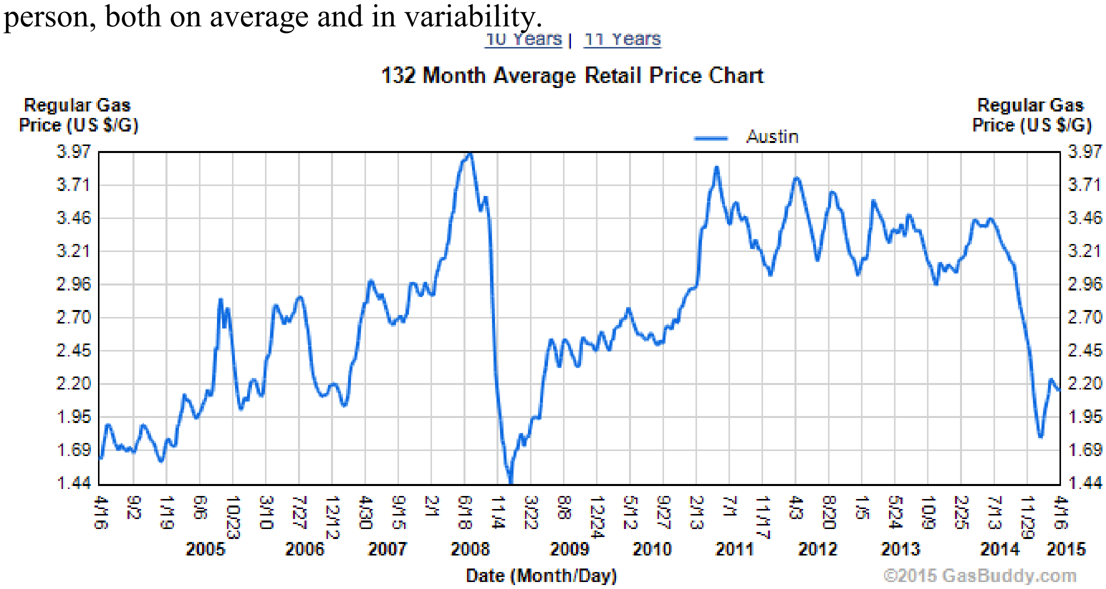

Figure 6: Changes in gasoline prices (87 octane) in Austin, TX, from 2005 through 2015.

TAX IMPLICATIONS OF VEHICLE ELECTRIFICATION

One additional factor to consider is the current series of structures to maintain roadways, and other infrastructure. Currently, Texas uses gasoline taxes to cover schools ($0.05 / gallon), and highway maintenance ($0.15 / gallon), as well as fees in motor vehicle registration. The federal government also taxes gasoline sales at a rate of $0.184 / gallon (Texas A&M Transportation Institute, 2011). Transitioning to EVs would reduce the funds associated with fuel taxes, and therefore one might want to consider means of recouping those costs. If one were to use the national average of 13,476 miles driven annually (US Department of Transportation, 2015), that would lead to a driver paying an annual rate of $86 towards federal, state highway, and state school funds (for a higher efficiency, 60 MPG vehicle), to $134 annually for a low efficiency vehicle at 15 MPG. When one considers the effects of parallel hybrid vehicles that achieve 45+ MPG, a diminishing return in tax revenues are already noted. Using the EPA MPG equivalent (MPGe) for a variety of vehicles from www.fueleconomy.gov, this indicates a steep diminishing return of tax revenues as MPG grows. A vehicle like the Tesla P85D can be expected, based on an assumed MPGe model, to pay 1/3 the annual taxes to Texas and the federal government that a Honda Civic driver would pay, although at this time the Tesla driver is not paying these fees at all, as no fees are recouped from these highway funds from the driver's electric bill or vehicle registration fees.

If one were to take the standpoint that societal equity would be created by having electric vehicle drivers pay annual taxes at the same fuel proportions per mile to state and federal governments, this would mean a Tesla driver (at 93 MPGe) would pay annually $21.73 to Texas highways, $7.25 to Texas schools, and $26 to the federal government. This would correspond to a roughly 10% increase to $0.115 in flat rate electricity prices.

Several different alternatives to a per-gallon fuel tax are available, many of which will capture support needed infrastructure given increasingly efficient parallel and series hybrid electric vehicles, and battery electric vehicles. It seems that a per-gallon fuel tax may no longer be the proper mechanism for supporting education and roadways, given the overall trend of vehicles towards greater efficiencies. Other novel approaches, such as flat fees at the time of sale and annual registration, a tax on vehicle miles traveled, or future public-private partnerships around road maintenance are options that may better maintain infrastructure in the light of growing per-mile vehicle efficiencies (Whalton & Hall, 2012).

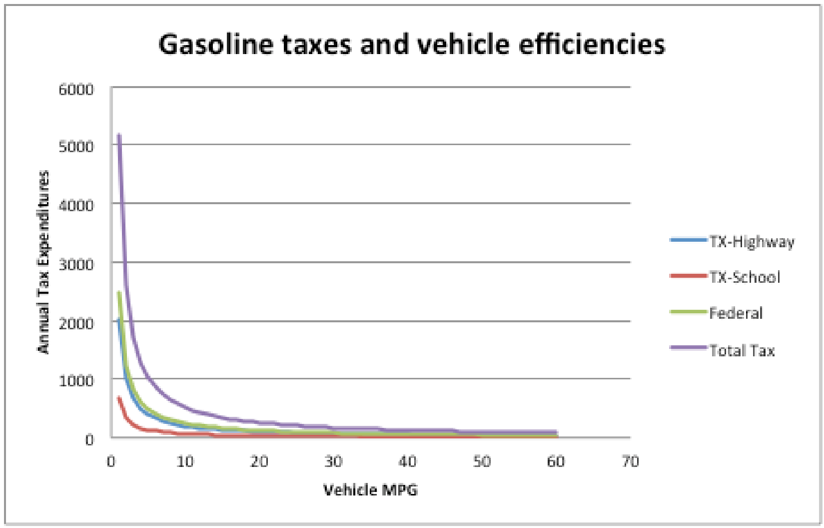

Figure 7: Gasoline taxes and vehicle efficiencies (presuming 13,476 miles/year)

2015 Vehicle	MPG / MPGe	Annual Taxes (if charged per MPGe)	Efficiency (kWh / 100mi)	kWh / year	Annual cost at $0.11/kWh
Honda Civic	33	$156.81			
Chevrolet Volt - gas	37	$139.86			
Honda Civic Hybrid	45	$115.00			
Toyota Prius	50	$103.50			
Tesla P85D	93	$55.64	36	4,851	$533.65
Chevrolet Volt - electric	98	$52.80	35	4,717	$518.83
Chevrolet Spark	119	$43.49	28	3,773	$415.06
BMW I3	124	$41.73	27	3,639	$400.24

Table 1: Projected tax revenues of specific vehicles based on MPG/e (presuming 13,476 miles/year)

Psychological Factors associated with Electric Vehicles

Traditionally, the bulk power system was thought of as a "predict, command and control" system, in which consumers of electricity were seen as being comprised of predictable and stochastic elements, but with no interaction other than serving their anticipated load. In order to transition to a bidirectional relationship between grid operator and energy consumer (and thus in this case vehicle driver), a series of psychological factors must be considered and engineered into the system.

SITUATIONAL AWARENESS

Both at the ISO and at the end-user level, situational awareness is a key factor in decision making, as a loss of situational awareness significantly increases the probability of a decision that is to the detriment of the bulk system. Situational awareness is classically defined as, "The perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status into the near future." Ultimately, situational awareness can be thought of as three components, from knowing the status of the situation and system (perception), to understanding the meaning of that status (comprehension), and ultimately the direction of that system into the near future (projection). Situational awareness is a concept thought of both at the individual and team level, as individuals attempting to communicate about a situation with different levels of situational awareness may in fact have different assumptions and thus have difficulties communicating or increased chances of errors due to misperception (Endlsey, 1995).

At the level of the grid operator, systems are explicitly developed and measured by their capacity to interface with end-users, and support situational awareness and decision making. One such example, Macomber Map, was developed to integrate a variety of core energy, market, model, outage scheduling, and GIS data so that control room reliability coordinators are able to build a strong situational awareness (Behr, 2010).

Ultimately, at the consumer level, the needs for situational awareness are somewhat different. All of the existing constraints, such as basecase or contingency thermal issues on transmission lines, do affect end-users, but the contribution of a single user to that concern is relatively small. Furthermore, the user's situational awareness should also include the profile of their own behavior, such as their real-time consumption, real-time or time-of-use prices, and other factors.

Strong end-user situational awareness would also merit the idea that a small change by a single user with good situational awareness may be insignificant, a single point lost in the large noise of the system. However, if that situational awareness and thus improved dynamic behavior were to scale across a neighborhood or other large population of users, the effects could be quite dramatic.

At the energy consumer level, several new devices, such as the current transformer-based eGauge (a circuit breaker-level energy meter), and advanced-meter interfacing displays offer the potential for end users to have a much greater sense about their energy use. As an example, simply giving end-users a meter measuring instantaneous whole-house consumption leads to shifting energy use off-peak, although not to significantly lower overall energy consumption (Sexton, Brown Johnson, & Konakayama, 1987).

END-USER MARKET UNDERSTANDING

At the transmission level, the energy market is a highly dynamic, fast-acting, and complex system, comprised of real-time and day-ahead pricing, markets for congestion revenue rights, renewable energy credits, and a great many other markets and systems. Nearly all residential customers in Texas are on flat-rate plans, so their energy usage is charged in the same way regardless of the time of day or state of the system, and thus they have little economic incentive (save altruism) to alter behavior to support the reliability or economic efficiency of the bulk power system.

Similarly, for most users, that limited understanding of the bulk power system means that decision making will be based on the economic structures to which they are exposed. From that perspective, energy decisions such as rooftop solar or vehicle electrification become focused on through monthly reductions in utility bills. While this trends in a positive direction both in conservation and environmental factors, it is not favorable regarding certain factors, such as the decision to use a flexible load device (e.g., vehicle charger) regardless of time of day. From an aggregate perspective, vehicle charging during times of daily peak demand on the system, such as in the late afternoon during summer months, can lead to increased costs spread across all users on the system, due to increased spot market purchases of retail providers (as load forecasts scramble to catch up with increased vehicle load), increased usage of units with lower heat rates on peak, and increased probabilities of equipment failures at the distribution level that lead to increased maintenance or replacements.

TIME DIFFERENTIAL DISCONNECT BETWEEN USAGE AND PAYMENT

From the perspective of operant conditioning (a method of behavioral learning in which reinforcements and punishments determine the subsequent probability of the behavior), one of the major factors that lead to reduced perceived connection between electricity consumers and their usage is in its large delays. This concept, termed delayed reinforcement, has been theoretically and experimentally shown to make learning new behaviors, or changing existing behaviors, far more difficult (Lattal, 2010). Therefore, if one can imagine making a single energy decision, which, along with all the other energy decisions over a 30 day period, leads to a utility bill, it becomes easy to conceptualize why they may continue making a series of disconnected decisions, given a reduced feedback loop.

In a modern-day case, retail provider Direct Energy has shown that daily SMS messages to consumers of the prior day's electricity costs (in dollars, not kWh consumption) leads to approximately 18% decreases in consumption (Khan, 2015). Therefore, by simply decreasing the time between the behavior and result, one can significantly induce behavioral change.

DISCONNECTS FROM STATUS OF TRANSMISSION, DISTRIBUTION, GENERATION SYSTEMS

Ultimately, energy consumers are generally unaware of the status of the generation, transmission, and distribution systems to which they are connected. One exception to this rule occurs at ERCOT, when physical responsive reserves drop below particular MW levels, leading to energy emergency alerts (EEAs). These EEA messages have been communicated from ERCOT to control centers for some years, and to the general public through media releases that are transmitted via radio, television, and online feeds. Since 2012, a smartphone application, the ERCOT Energy Saver, has been downloaded by over 20,000 users. The application allows both high-level information about the real-time status of the bulk system, and also allows for push notifications to end-users when ERCOT enters an EEA.

Typically, one would expect an EEA to correspond to significant increases in wholesale prices across part or the entire ERCOT grid, due to exceptionally limited remaining capacities, and such prices have become institutionalized through the Operating Reserve Demand Curve. However, consumers, typically on flat-rate pricing that does not reflect wholesale price variations, have no economic incentives to shed their load. However, through a variety of outreach efforts including the push notifications, significant behavioral changes at the residential and small C&I load levels have been observed, due to altruistic and mutually beneficial behaviors on the part of consumers, once this information became available to them.

This certainly does not mean that all consumers would be willing to reduce their energy use continuously. In fact, experimental evidence indicates a “fatigue effect’, in which continued messaging and behavioral change on the part of the user leads to an overwhelmed feeling, especially when the information in multimodal and about multiple aspects of life. Humans can be seen as able to thrive reasonably well on a dynamic system, but likely less so on a great many dynamic systems at the same time.

DISCONNECTS FROM EMISSION IMPACTS OF BEHAVIORS

Similarly, the relationship between an end-user’s energy decisions and a marginal change in air quality emissions are even more difficult to link. Adding or removing a load from the system will change the output at one or more marginal units, and the emissions associated with those increases will then be moved based on wind speeds, particulate sizes, presence of sunlight, and a variety of other factors. However, if the end user were to have more information about an energy decision, such as “charging your car now would lead to two nearby power plants to emit and additional X pounds of CO_2, NO_X, SO_X, and PM, and wind flows are anticipated to blow these emissions towards your home,” one could imagine the end user making a different choice, especially if those emissions would pass over their home as their children play in the back yard. If the wind flows would move the emissions elsewhere, it may be the case that a different decision would be made. This is, of course, a theoretical construct, and based on the assumptions that several complicated models could be summarized down to the individual consumer level, creating sufficient enough levels to garner their attention.

Reductions in emissions may also have further advantages for society, beyond energy. For example, presuming the 95% NO_X reduction highlighted in the Austin Energy study, transitioning 30% of city cars from ICE vehicles to electric vehicles would significantly reduce city-wide overall CO_2 emissions, and also eliminate any non-attainment issues.

AGENTS AND SITUATIONAL AWARENESS

The human inability to process large volumes of data from multiple dynamic systems leads to difficulties in controlling and predicting the overall functioning of a system. This facet of human function may potentially lead to the use of fully or partially autonomous agents acting on their behalf at the energy level, able to respond to real-time pricing and system conditions, engaging in behaviors that match the user's pattern of preference. For example, a user with a primary focus on air quality may choose to charge their electric vehicle when the proportion of renewables on the grid is quite high; another user with a primary focus on cost savings may instead charge their vehicle when the system (or at least the portion on which they are connected) is minimally congested and prices are lowest.

RANGE ANXIETY AND DRIVER MENTAL MODELS

Popular media frequently has used the term "range anxiety" to denote an electric vehicle drivers' fear that they will run out of charge, and end stranded or unable to take needed trips. Experimental data has found that range anxiety decreases with driver experience in their electric vehicle, due to improved mental models on the drivers' part about the functioning of their vehicle (Rauh, Franke, & Krems, 2015), likely in the same fashion that all drivers get to better understand and predict the function of new vehicles over time. Generally, fairly new electric vehicle drivers tend to prefer electric vehicle ranges significantly in excess of their historic daily miles driven (Franke & Krems, 2013), and have concerns around limited availability and charging times associated with DC fast public charging stations.

From another perspective, range anxiety and its tendency to shift can be thought of from the perspective of changes in the mental model of the driver. Over time, as a driver is exposed to the use of their electric vehicle and availability of home, work, and/or commercial charging, their internal representation of their electric vehicles tends to become more granular and refined. Based on measured patterns of electric vehicle driving between 2011-2014, it now also appears that EV batteries can be expected to support driver needs at or below 70% of nameplate capacity, indicating a need to refocus on driver patterns and needs more than an abstract capacity figure (Saxena, 2015)., as well as potentially new inputs around the placement of EVSEs (Chen, Kockelman, & Khan, 2013)

Overall, range anxiety can be thought of as affecting the drivers as a complex system, including perceptions of range buffering, the availability of resources to assist with range insufficiency, and stress indicators across all layers of function (Rauh, Franke, & Krems, 2015)

As is the case in the management of the bulk power system, human errors associated with EV driving can come from the application of the incorrect mental model. One recent example is with electric vehicle drivers in Atlanta, GA, near the North American Electric Reliability Corporation's headquarters. Thanks to tax incentives at both the federal and state levels, there are a great many Nissan Leaf vehicles in Atlanta, and high speed ChaDeMo stations throughout the city. Some drivers are able to lease their Leaf BEVs for less than $75/month, which when incorporated with fuel savings and potentially free workplace charging, becomes quite attractive as compared to ICE alternatives. However, one of the interesting noted phenomena in Atlanta is that, in the winter, several Leaf drivers run out of range and require tow trucks or to stop and charge en route to a destination. It is an interesting study on the application of incorrect mental models.

In an ICE engine, climate control leverages the ICE engine and its function. Therefore, in the winter, when a driver turns on the defogger or cabin heater, waste heat from combustion is siphoned off to provide heat as needed; from an energy perspective, this means an increase only primarily in fan speeds. In the summer, air conditioning use is more energy intensive, due to the need to increase engine RPM to power the compressor and cool the vehicle. In an electric vehicle, the opposite is true; electric cooling is generally less energy intensive than electric heating (which is essentially resistive heating, except for the recent BMW BEV model, which uses a more efficient heat pump). Therefore, drivers presume their ranges will change less in the winter than they actually do, leading to issues in forecasting total vehicle ranges.

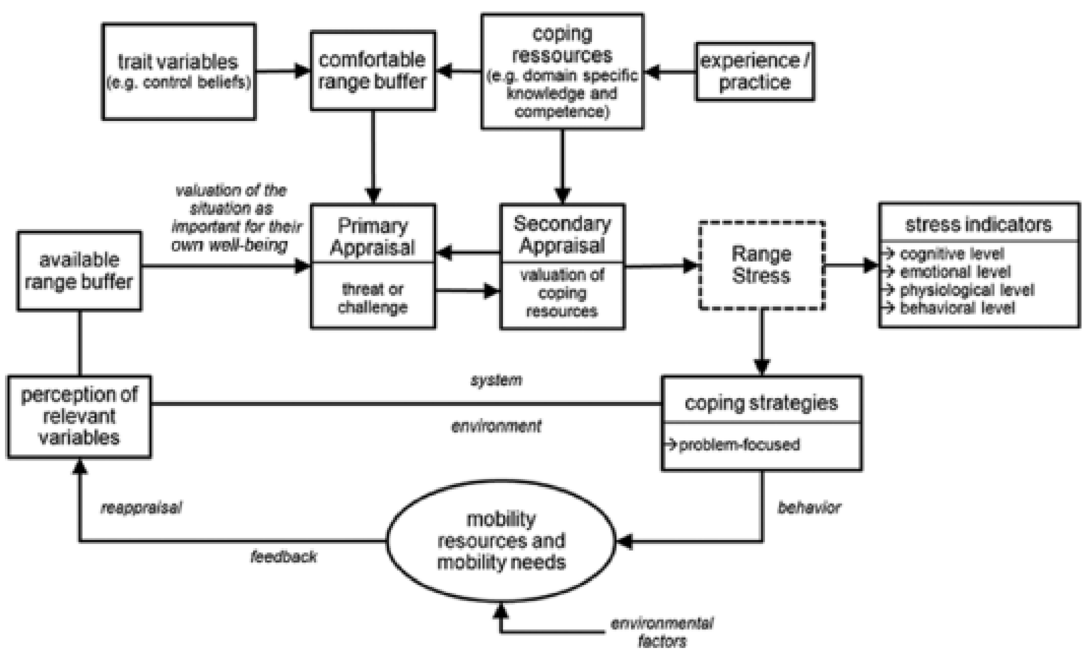

Figure 8: A psychological framework of range anxiety (Rauh, Franke, & Krems, 2015)

"Curse of the default"

One of the major challenges to adoption of any new technology has to do with the preponderance of users leaving the technologies in their original, or near-original configurations. In the early days of remote garage door openers, this meant that dip switch-based openers were set to '000000' leading to several rashes of thefts, given off-the-shelf openers could open garage doors. When looking at web browser users, users who indicate that they would prefer not to be tracked as they browse across the web are not very likely to have enabled their browser's 'do not track' header feature, which exactly accomplishes that function. That is why changes in defaults, like Firefox's switch from Google to Yahoo as the default search provider, are seen as having tremendous market shifting power (Lunden, 2015).

When applied to electric vehicles, this means that the vast majority of electric vehicles can be expected to behave exactly in the same configuration as they had when they first leave the dealership lot, meaning that today, they are likely to charge immediately on plug-in, which typically increases aggregate on-peak load for charging starting in the early evening, particularly in regions that have heavy early evening air-conditioning use. Therefore, if vehicle control is not seen as a near-term viability, it is strongly recommended that part of the final interactions with the dealership before leaving the lot include programming the vehicle to charge off-peak, or programming to do so at the factory.

Moral self-regulation and pro-environment / pro-reliability decisions

One of the interesting facets of human behavior is that, while it's far easier to think of human decisions in an independent, probabilistic fashion, real-world behavior tends to be more linked between decisions. For example, the phenomenon of moral self-regulation describes a person making a decision they believe to be kind, moral, or environmentally friendly, which paradoxically increases the probability they will, in short order, make an unkind, immoral, or environmentally harmful decision. Interestingly, this seems to be heavily related to one's perception of self; affirmations to moral identity increase the probability of an immoral behavior, while threats to moral identity lead to more moral behaviors, presumably to re-acquire the sense of moral self-worth. Across many empirical and experimental studies, these phenomena are both observed and affected by these moral perceptions (Sachdeva, Illiev, & Medin, 2009).

This phenomenon can be especially interesting moving towards a smart grid world, in which user behaviors on highly dynamic systems can cause instabilities. It means that not all LEED-certified buildings may use significantly less energy than their equivalent non-LEED counterparts (Newsham, Mancini, & Brit, 2009), EV drivers with rooftop PV may be more likely to lower their air conditioner cooling set points or leave their doors opened, or any other number of behaviors that lower the efficiency of a system from its theoretical maxima.

SOCIAL AND FINANCIAL DOMAINS

Furthermore, from a behavioral economics perspective, one can think of two separate domains of function, one social exchange, and one financial exchange. We tend to think of activities in either realm, but crossing from one to the other (especially social to financial) can also produce unexpected results. As an example, at a daycare center in Israel with frequently-late parents picking up their children, a late fine began to be assessed after baseline tracking. While this was intended to curb lateness, it had the opposite effect, in that parental tardiness increased significantly and did not recede when the fines were removed.

While some view the fines as being insufficient, it appears a subtler shift happened with the parents: beforehand, while sometimes late, parents had a cognizance of the social factors associated with their tardiness. The teachers were not able to go home to their families as quickly, or were otherwise inconvenienced, and often late parents frequently apologized despite being late. After enacting the fine, it appears that these parents shifted their thought process about their lateness from social exchange (being part of a society shared with the teachers and administrators) to a financial exchange domain (fee for service). Once in the financial domain, the parents were performing far simpler cost-benefit analyses around their behavior. Through that lens, a higher fine might produce less tardiness, but still weaken the empathy and sense of community that the parents had with their teachers (Gneezy & Rustichini, 2000).

Constraints on the distribution system

DISTRIBUTION TRANSFORMER THERMAL MANAGEMENT

The vast majority of distribution-level transformers in the United States operate as passive devices, not providing telemetry to its owners. Instead, their operational states are based on simulations and observations of load profile curves, with many assumptions. For example, in Texas, the presumption is that the transformers would be sized to support the peak load of a summer afternoon, with the presumption that over midnight to early morning, the transformer would be in a cool-down period. Electric vehicles have the potential to violate these assumptions, either adding significant additional load on peak due to drivers arriving home, starting their vehicles charging and then adjusting their air conditioners, or charging their cars overnight and reducing the cool-down periods. This can be exacerbated by the cluster effect, which relates to increased probabilities of neighbors being similar to you; thus, if you plug in an electric vehicle when you come home from work, there is a strong chance your neighbors will have electric vehicles as well, and plug them in when they return home from work.

Distribution providers tend to continue with existing mental models, treating low voltage transformers as passive elements on the system. Should a distribution transformer fail, one would expect an AMI to signal the loss of voltage, leading to a truck dispatch to repair it. Should that be the case due to increased EV load, one might assume that simply adding a larger-capacity transformer solves the issue.

However, the approach of continuing to grow the capacity of the system for infrequent use, rather than engineering controllable portions of the peak load to off-peak times, may in the long run lead to significantly higher costs of building and maintaining the system in the typical context where costs of transformer replacement are socialized broadly, whereas the benefits of increased capacity accrue to individuals. In order to better understand the capacities at the transformer level, therefore, one would require additional telemetry from the transformer, likely measuring real and reactive power, as well as thermals in the transformer. One could also think of additional benefits for the distribution provider, such as a simpler means for identifying unauthorized and parasitic taps on the system, when the aggregation of AMI 15-minute data is significantly lower than the transformer's 15 minute load data.

POWER FACTOR VARIATIONS AT DISTRIBUTION TRANSFORMERS

One recent insight on distribution transformer data has come from Pecan Street Project's research in the Mueller neighborhood, indicating significant variation in the direction of MW flow across the day, due to rooftop photovoltaic panels, and thus a significantly changing power factor at the transformer level (Toliyat, Kwasinski, & Uriarte, 2012). Based on that assumption, the development of a distribution system operator (DSO) can be thought of as incorporating measurements at the low side of a distribution transformer, in order to determine the status of the system on which multiple homes are connected (Carvallo & Cooper, 2011), thus incorporating the state of both the transmission and distribution systems. These costs of reactive power support have been suggested for some time (e.g., (Lamont, 1999)). However, given increasingly dynamic systems due to distributed energy resources, additional loads like electric vehicles, and other factors, reactive power needs may change often, and thus some future form of pricing signal might provide an effective means to reducing their swing.

HARMONIC FACTORS WITH LARGE PROLIFERATIONS OF POWER ELECTRONICS

As the bulk power system moves to a much more dynamic system, several different factors could potentially come together to increase harmonic content on the system. Power electronics, devices that utilize high-speed switching to convert between DC and AC, change voltage levels and more efficiently control motor loads, and also have the byproduct of rapidly changing load profiles. Power electronics have the potential to create predictable harmonics at the PV inverter level (Ngo & Santoso, 2014), and in a variety of different applications, including at the electric vehicle level, where power electronics determine the rate at which batteries are charged. Multiple interconnected pulsed width modulation (PWM) drives can potentially aggregate together and create large harmonic currents.

Similarly, energizing a capacitor bank has the effect of a short-term series of harmonics on the system. If one considers a situation where most consumer electronics may use power electronics to convert between different voltages, between AC and DC, or to serve motor control functions, and intermittent renewables lead to the need for varying reactive power on the system (and thus more switching such as in a static var compensators), one can imagine a system with swings in harmonic levels, especially at times of significant change in generation or load.

Vehicle to Grid Integration Issues

LOCAL RESPONSE OF ELECTRIC VEHICLES

In order to ensure the reliability of the bulk power system, and in situations where control signals cannot reach the equipment, devices need to have the capacity to independently change their functionality based on local measurements of the state of the system on which they are connected. This can occur, for example, with a device that can detect when the system moves outside its normal range of function. As an example, a charging electric vehicle that detects frequency drop below some set point (for example, 59.8 Hz) should reduce or delay its charging, to give the system room as local generation is ramped up to rematch system-wide load. Similarly, one could imagine an EV or EVSE deferring charge when the system harmonics cross a certain THD threshold, thus protecting the vehicle from transients on the system.

SYNCHROPHASOR INTEGRATION: LOCAL AND REMOTE

Modern-day electric vehicles are quite sophisticated and connected devices. Given the functionality that EVs have, including battery charging management, GPS navigation, and cellular data and voice connectivity, one could imagine utilizing these features with additional AC waveform analysis, providing GPS time-stamped synchrophasor measurements back to an aggregator or utility. Aggregation of these points could potentially build an interesting view of the overall status and health of the system, all the way from transmission to distribution level. This would also offer additional early-warning indicators about common distribution-level issues, such as transformer tap changer difficulties, and about other equipment that may be transmitting harmonic currents and voltages on the system.

While this information is likely not directly helpful (and in fact due to information overload potentially a risk) to the grid operator to maintain, a distribution system operator could serve to aggregate this data, and create automated behaviors based on multiple synchrophasor measurements. For example, a growing angular divergence between two electric vehicles could indicate a fault on the system, and thus lead to some automated action on the part of the vehicles, such as a 20 second pause of charging. Of course, these same functions could also be carried out at the low side of the transformer, although leveraging the existing technologies already in the EV and many EVSEs may offer a reduced cost for acquiring that data.

Special question – businesses with backup power or microgrids

From the perspective of city management, a ton of CO_2, SO_X, or NO_X, whether generated by a coal power plant, from an ICE engine's tailpipe, or from a data center's diesel backup are considered nearly identical, as they are all measured and all can aggregate to non-attainment and climate-concern levels. From a statistical standpoint, the varying levels of informational availability may lead to disparities in terms of data collection and root cause comprehension. For example, should a data center with a diesel generator choose, based on spot market prices, to disconnect from the grid and transfer their load to their generator, they are free to do so. However, estimating the impact of policies both at the regulatory and grid management levels that change the probabilities of such events are also of great importance to the city trying to maintain its overall CO_2 footprint below a certain level. An electric vehicle providing synchrophasor telemetry may be able to at some degree show changes in phase angle not replicated by other nearby EVs (thus indicating a potential islanding event or transfer to a different circuit). This would allow for better understanding of the dynamics of distribution circuits and how they are integrated into the system. This is especially interesting around data centers, considering how the move towards cloud computing has lead them to be some of the fastest-growing load tranches (Howland, 2014).

LIMITED COMMUNICATIONS PIPELINES BETWEEN VEHICLE, SUPPLY, AND SYSTEM

One of the concerns around integrating electric vehicles and the bulk power system is around the limited communications pipelines between the two. The current J1772 specification supports a very limited exchange of information between the vehicle and charger, namely safety and maximum charge rate in amps. Some vehicles and chargers are compliant with open standards such as OpenADR, but not most. Closed and proprietary systems at both the vehicle and charger levels further make integration across a wide area of devices far more difficult, and unknown black box systems, with multiple vendors with financial incentives to over-market their products may lead to unrealistic timing, reliability, or control estimates, thus damaging overall model accuracy. Ultimately, in order for these systems to connect to the power system from the market services perspective, reliability statistics need to be far better understood, and end-to-end testing with transparent data acquisition is needed. Ultimately, this data would lead to more accurate models (and thus likely better compensation to the providers), as well as additional protections to the user, ensuring those vehicles have sufficient charge when needed.

ON-PEAK CHARGING

Generally, uncontrollable load systems are engineered to offer sufficient capacity at peak levels. Within the ERCOT region, Texas climate has yielded the primary predictive factor for system load temperature. For example, contrasting two days, one a mild day (Dallas temperature 64° F, March 9, 2011), and a hot day (Dallas temperature 109°F, August 3, 2011), the largest increase in load was from the residential sector, which increased fourfold. Similarly, when analyzed at the residential level on a hot August day, circuit-breaker level data indicates the vast majority of home energy use is associated with temperature control, with additional smaller components in the late afternoon associated with homeowners activities, returning home from work (ERCOT, Inc., 2012).

If one were to supplement the household peak in the afternoon (approximately 6 kW) with a level 2 charging station (typically running between 3.3 and 7.2 kW), one can imagine a significant increase in distribution transformer loading at those peak times. Such effects were typical in studied communities with electrified vehicles, in which EV charging tended to begin at approximately 4 PM, peaking approximately 8 PM on weekdays. Interestingly, time of use pricing participants instead ramped at 12 AM, and peaked at 1 AM, attributed to the change in pricing tier at those points, creating an economic incentive for drivers to program their vehicles to defer charging to those times (Schey, Scoffield, & Smart, 2012)

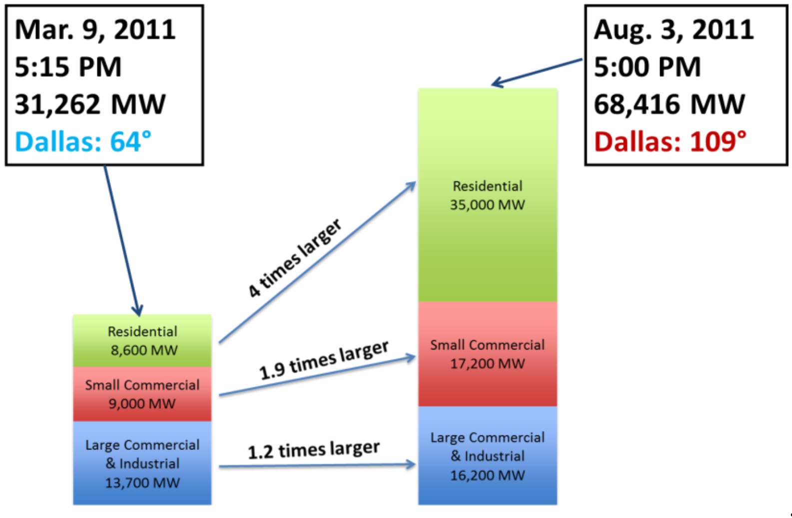

Figure 9: An example of ERCOT system load based on ambient temperature

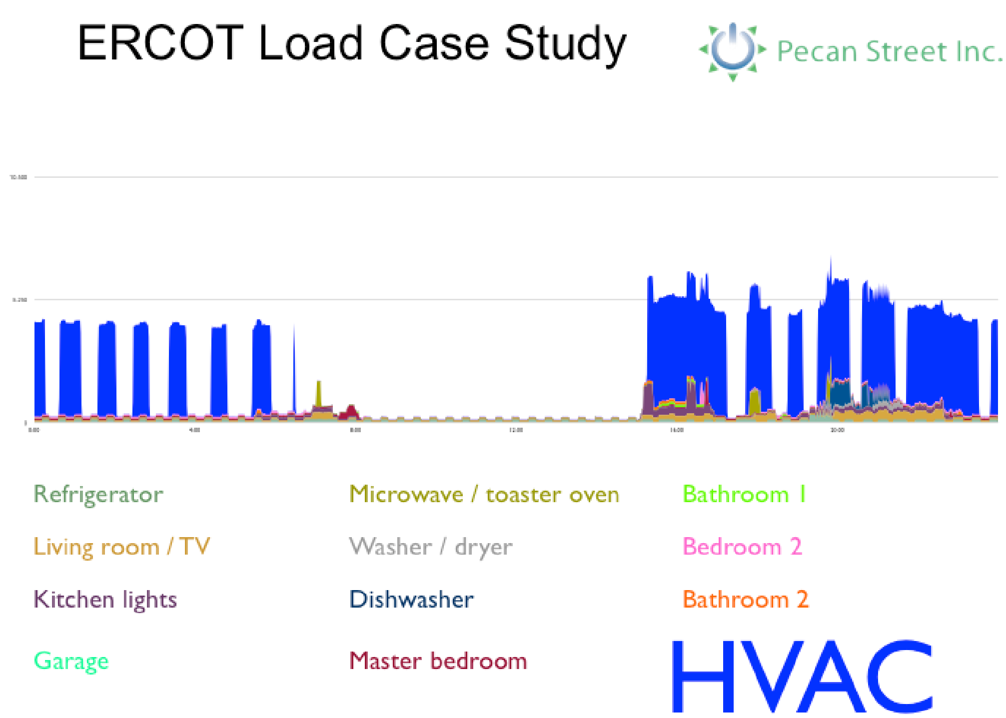

Figure 10: An example of residential load on a high temperature day

Line Capacity issues on peak

One of the major sources of locational marginal price growth on the transmission system has to do with the limited carrying capacity of transmission lines. As transmission lines carry more electricity, thermal factors associated with the transmission can lead to the line deforming if heated for sustained intervals. Therefore, security-constrained economic dispatch approaches lead to market signals engineered to induce behaviors that will prevent lines from being at those levels for long durations.

Similarly, in order to maintain the reliability of the bulk power system, the grid operator is directed to maintain the system to be able to withstand a N-1 contingency event, meaning that the system can maintain proper function after any single failure of generator, transmission line, transmission level transformer (NERC, 2012). Recently, in the ERCOT region, further modeling of loss of reactive support devices (capacitors, reactors and static var compensators) are also being studied.

When one considers the possibility that a large scale growth of electric vehicles could all hit the transmission system at the same time on a high temperature day with significant HVAC load, one can become concerned both about the security and economics of maintaining the bulk power system function. From a perspective of social equity, devices that can potentially be shifted (a vehicle charged starting at 6 PM or 12 AM, provided it has sufficient time to charge fully, is not differently charged in the early morning) should be encouraged to load shift, while other devices that are less easily shifted perhaps should be allowed to function. The impetus for this shift could come from differential pricing models from the market signals perspective, or grid or locally-controlled behavior from the smart grid perspective.

One of the interesting phenomena that occurs on a power system is that sometimes, increasing load at a particular point will actually reduce the flow on a particular transmission line. Therefore, controllable loads such as electric vehicles can be thought of as providing potential reliability-strengthening behaviors, both in increasing and in decreasing load, although proportionally, is it anticipated that the ratio is heavily tilted towards load curtailment, and away from load augmentation.

Distribution transformer overheating on peak/loss of cool-down off-peak

Typical distribution transformers are run as unintelligent devices, simply changing from higher distribution-level voltages to residential levels, whether as three-phase 480 volt, or single-phase split 220/110 volt systems. It seems as though the general trend is to see these devices as replaceable, with indication of device failure partially automated through its downstream advanced meters reporting outages. As passive devices, the transformers are expected to work by providing increased flow-through on peak, which include generation of waste heat from internal resistances and other losses. As with other devices, this heat can build up and shorten the lifespan of the transformer's coils, oil, core, or other components, and other factors, such as low oil levels, can exacerbate the problem. In a traditional system, on-peak use on hot days would lead to increased thermal loading on the transformers, with cool-down periods overnight as home energy consumption drops overnight. Shifting electric vehicle charging from on-peak to this cool-down period may in fact better support the transmission system or system-wide energy prices, but potentially at the expense of reduced distribution transformer life compared to non-EV serving transformers. However, this shifting behavior is still preferable to both on-peak HVAC and EV loads, for economic dispatch, emissions, and reliability concerns.

Generators exceeding EPA emissions limits

Another factor to consider about electric vehicle charging integration with the distribution and generation system has to do with the generation fleet. In Texas, south-facing photovoltaic panels tend to generate electricity peaking in the early afternoon, several hours before the ramp-up of home energy consumption due to HVAC, vehicle charging, and other energy demands of residents returning home from work. Overall, these south-facing systems cut peak demand by about 54%, while a change in orientation to west-facing leads to a greater peak demand reduction of 65%, even with overall annual reductions in total generation (Pecan Street Project, 2013) .

While this trend is impressive, vehicle electrification also adds an additional constraint on the system. If one imagines vehicle charging being conducted off-peak, in Texas the energy sources powering the vehicle charging can be thought of as mixed between West Texas wind, which generally peaks overnight, base-load coal generation, and natural gas generation. Many of these plants have run with the expectation of lower generation levels over night. Increasing their output at these times may not affect the system in terms of congestion, but for those units powered by fossil fuels, increased annual production levels will be expected to lead to increased emissions. Given that fossil fuel plants have emissions limits, one could expect permits to violate limits in emergency situations such as reliability-must-run scenarios, but not likely on a daily basis to cover increased generation associated with increased electric vehicle charging. If in fact the reductions in CO_2 emissions due to shifting away from ICE vehicles lead to increased CO_2 emissions at the plant level, a further investigation to the total cost to society of the generation emissions limits (as they now are including vehicle emissions as well) should be considered.

"Birthday cake" curve

When one looks at the profile of a home with its HVAC activated, one notices a large curve (most often, the largest intermittent household load), as the unit turns on and off. It is often the case that an individual will come home from work, and the act of their coming home, turning on their HVAC system, lights, cooking, etc. This leads in aggregate to a peak load demand. At the household level, if one also charges an electric vehicle, this leads to a combined jump in load during the time that both the EV and HVAC are active.

Given the cluster effect, this means that an EV driver who is likely going to come home, turn on their HVAC and start charging their car, is also likely to have many neighbors who do the same. This curve, as demonstrated in Figure 11, may also be an underestimation; it was collected by Pecan Street Project in 2010, and based on its 3.3kW load, is likely a Nissan Leaf or Chevrolet Volt. At the time of this writing, many electric vehicles maximum charge rates are higher (7.2 kW or more for the Tesla Model S, 6.6 kW for the Nissan Leaf, Ford Focus Electric, and several others).

From the implications both to the distribution transformers and the overall grid during peak hours (especially summer heat-related peak), this on-peak charging has the risk of leading to significant issues from both grid reliability and distribution-level reliability.

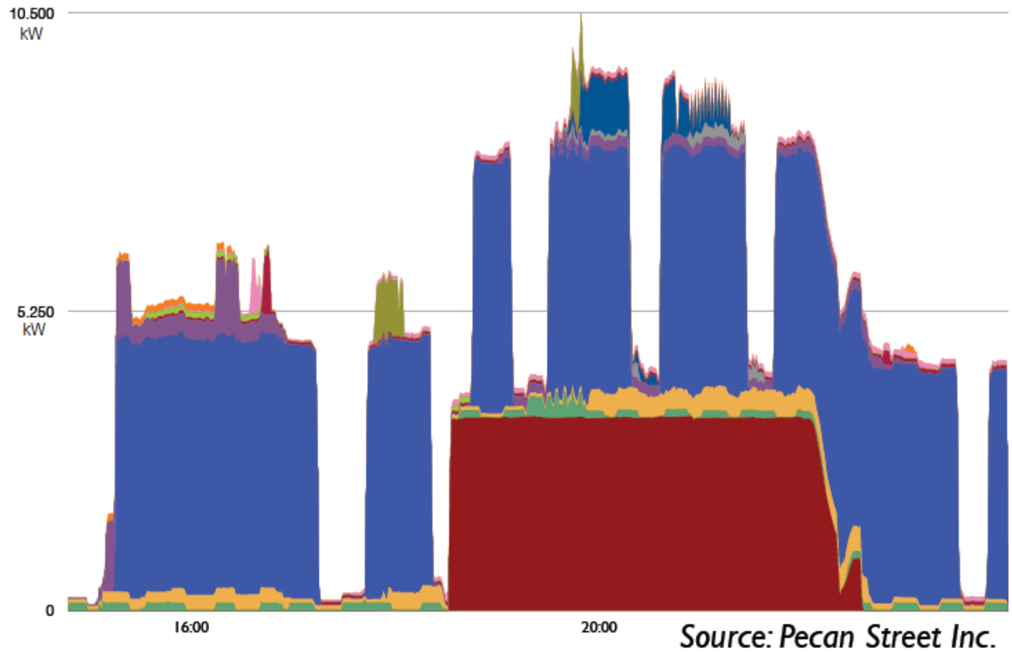

Figure 11: The Birthday Cake Curve, with on-peak EV charging (red) and HVAC usage (blue)

ERCOT Electric Vehicle to Grid Integration Research

The approach of using electric vehicles to balance renewable generation has been tested as part of ERCOT's electric vehicle to grid integration, since 2011. Currently, this research project consists of several EVSEs at both ERCOT's Taylor, Texas facility, and its Austin, Texas facility. Both sites additionally include eGauge devices, measuring power use per circuit, at a 1-second resolution. Additionally, the Taylor installation has a 5kW PV array. By sending demand response signals to an EVSE every minute, one can roughly charge an EV under a PV array's generation envelope. While sounding simple in theory, there are several practical limitations with this approach

The ultimate goal of integrating electric vehicles (at the vehicle and/or EVSE point) with the bulk power system is to provide the appropriate levels of controllability of EV charging in order to support both economic efficiency and to enhance the reliability of the system. A very simple example of such a behavior was conducted at the ERCOT EV research test bed, during which over the course of a day, a 2011 Chevrolet Volt was sent (via EVSE) a one-minute max charging rate signal, based on the average generation levels from the test bed's 5 kW photovoltaic array. As shown in Figure 12, while overall charging trended towards the PV line, vehicle response tended to lag behind with high variability, attributed in part to the black box network surrounding the EVSEs and network lag. Furthermore, given the substantial variability of PV generation during the experiment (it was a day with some cloud covering and high wind moving the clouds quickly), a one-minute average failed to fully compensate for the variability of the generation curve. In order to alleviate that variability, one might need to add some capacitors on the DC side of the solar array, or use some other strategy to better smooth out the generation curves.

Subsequent experiments have shown far more reliable charging behaviors when the time ranges are shortened, and the control loop is more integrated. For example, in this study, a server located in Austin read from an eGauge in Taylor (over a Sprint data connection) to determine the last minute average generation, which in turn led to a signal being sent to a control center in California, which is then rebroadcast back to Taylor via an AT&T cellular connection.

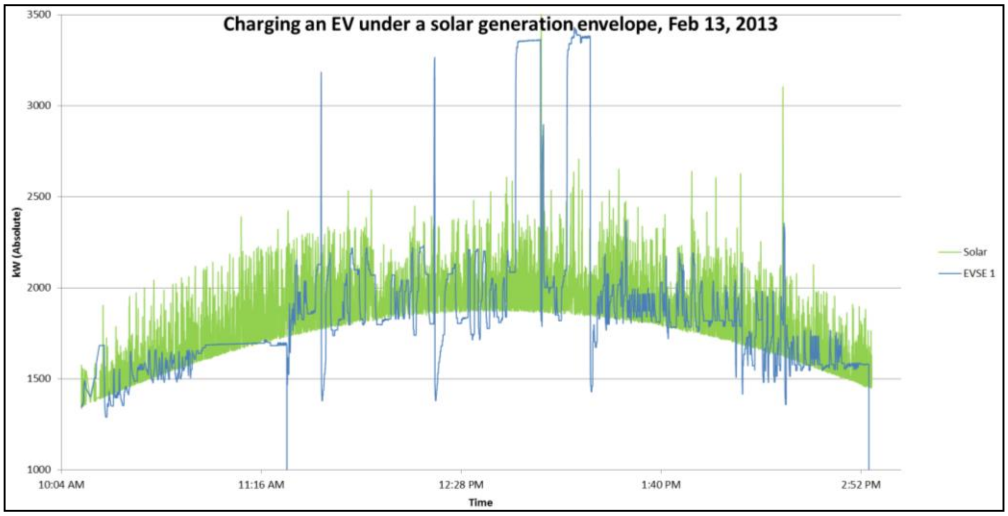

Figure 12: An example of EVSE remote control to charge an electric vehicle under a PV envelope

It is also the case, as shown in Figure 13, that internal vehicle controls may not behave as intended by the controller. In this example, a 2015 Nissan Leaf was instructed to charge at 10% (0.6kW), but instead chose to not charge at all. When instructed to charge at 25% (1.65 kW), the vehicle instead chose to charge at 1.5kW, but only after being first allowed back to the 6.6kW full rate for a brief period of time. This is partially attributable to the J1772 specification, in which the EVSE is actually modulating a pulse width signal to indicate maximum charge rate, with some discrete set of values, but it also attributable to logic on the vehicle side, likely optimized to maximize battery life or some other function, which may not always align with rapid charge rate response to the maximum rate as specified by the controller.

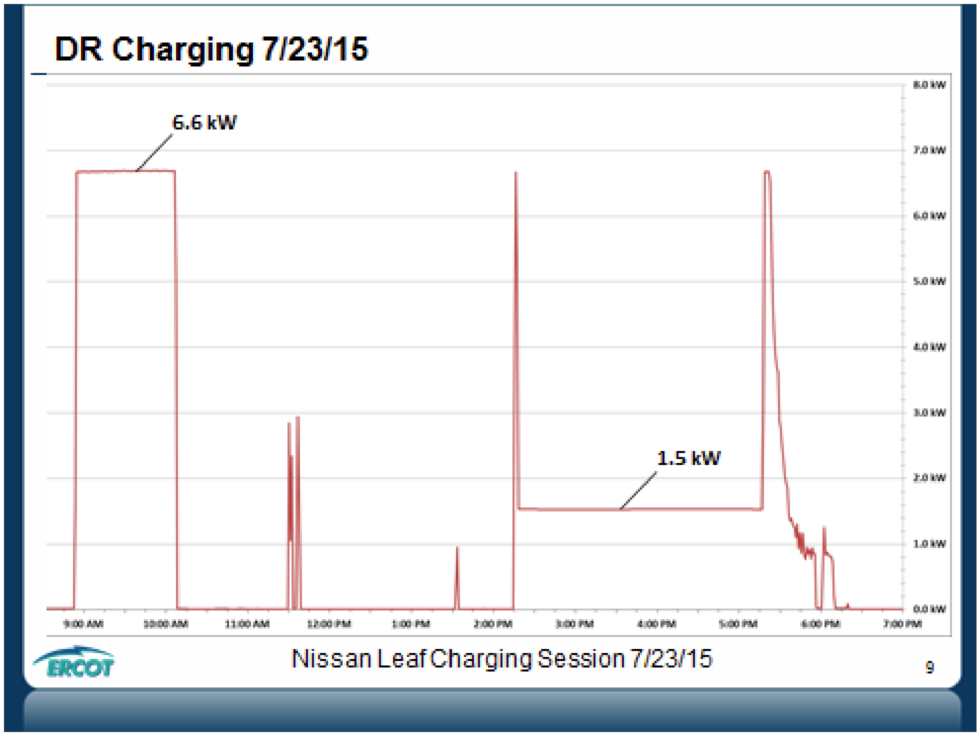

Figure 13: Nissan Leaf response to varying levels of DR commands

"Duck" Curve

A fascinating trend has started to emerge with systems in California and Hawaii, both with strong incentives and rollouts of distributed photovoltaics. This "duck curve" leads to significant drops in system net load from late morning to early afternoon, due to large proliferations of behind-the-meter PV generation. In contrast to ERCOT, both Hawaii and California have more modest penetrations of air-conditioning load. This can lead to issues at the distribution transformer level (e.g., heating due to real power upflow), potentially negative load at the transmission interconnection point, and at the transmission level changes in congestion patterns on the system, as well as leading to situations where base load plants do not have sufficient demand to stay online at minimum MW levels. These offlining units can lead to concerns about reliability support later in the day, or the possibility for needing rapid ramping of both real power flow and direction should clouds occlude an area. From the California perspective, if the trend of rooftop PV panels continues at the current rate, it could lead to potential system over-generation by 2020, or over 13 GW of needed generation ramping within three hours.

This phenomena also has interesting human factors questions associated with it. Energy users, especially in places like California, are used to receiving messaging about not using unnecessary loads during peak times, instead delaying the load to off-peak times in the evenings. As these people are not home during mid-day, they are less likely to allow their washing machine to run (the clothing may sit for hours waiting to be transferred to the dryer), cannot charge their electric vehicle, and are encouraged not to use their pool pumps. Now, with this new issue, some of these messages to Californians may in fact begin to shift, although it is unclear that there is sufficient elastic load available in the system mid-day. This may lead to increased incentives for energy storage, or additional subsidies for research and development.

As with many intersections between the engineering of the bulk system, the development of its markets, government policies and incentives, and human behavior, the duck curve problem highlights the need to plan ahead for the proliferation of devices, and in an increasingly dynamic way, leverage the total of uncontrollable generation assets and controllable load and generation assets to balance the system. Furthermore, it highlights the need for a more holistic and anticipatory view into future system planning from an overall integration standpoint.

Generalizing from the examples above, one could imagine scaling out California's workplace EV charging, adding controls to have vehicles charge and modulate against the distributed solar resources in the state. This has an interesting effect in theory, though, as essentially it uses the distribution system as a generation aggregation asset, not just a load serving asset. While it may be a good solution in California, it is likely less viable in Texas, given the additional exacerbation of peak load associated with EV charging on peak.

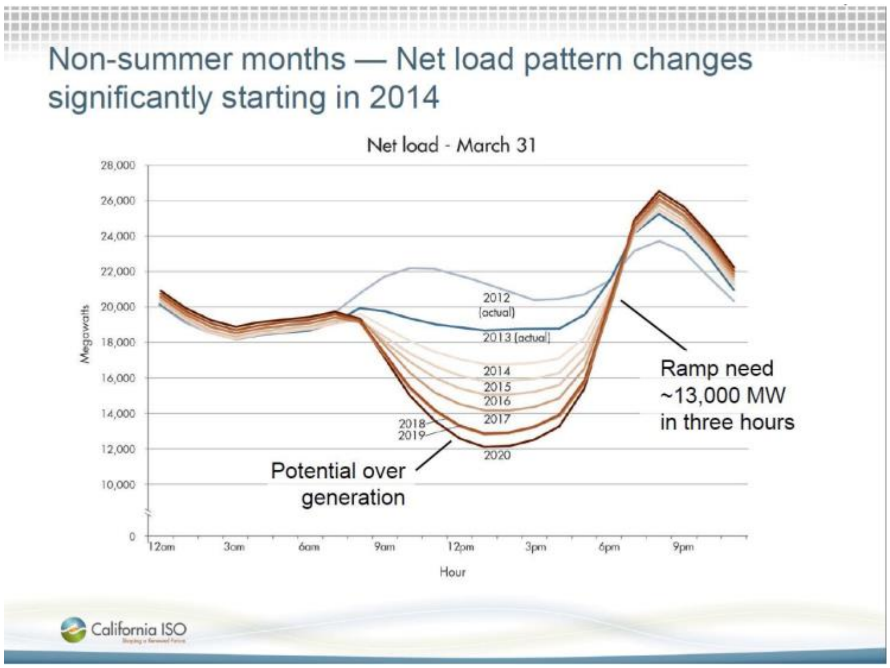

Figure 14: The California "duck curve" as a result of DER growth

CHAPTER 3: METHODS

The goal of this research was to take the parameters associated with grid-level generation, and simulate a variety of scenarios in which distributed energy resources, centralized renewable generators, microgrid-level SOFC generation devices and controlled electric vehicle charging can be modulated to alter both the emissions per-mile driven, and the overall carbon footprint of the combination of electric power generation and light transportation.

The approach used in this research consists of an agent-based model, simulating a neighborhood and its combined electric power and automotive transportation emissions. Several different agent components were created to anticipate individual driver and household behaviors and their associated emission and financial costs. The model was designed to allow for significant flexibility. Some of the parameters were designed for distributions against a Gaussian curve (e.g., the mean and standard deviation of cars per household, or PV array capacity).

This chapter includes a detailed analysis of the inputs to the simulation, including an overview of the simulation's user interface and controllable parameters. It then discusses the components within the agent-based model, including the home (with PV installations) and vehicles, and provides a detailed overview of the agent-based modeling approach. It further details the steps of analysis conducted during each hour, as well as a discussion of the assumptions made during the analysis process. It concludes by reviewing the permutations of analysis conducted over the course of this research.

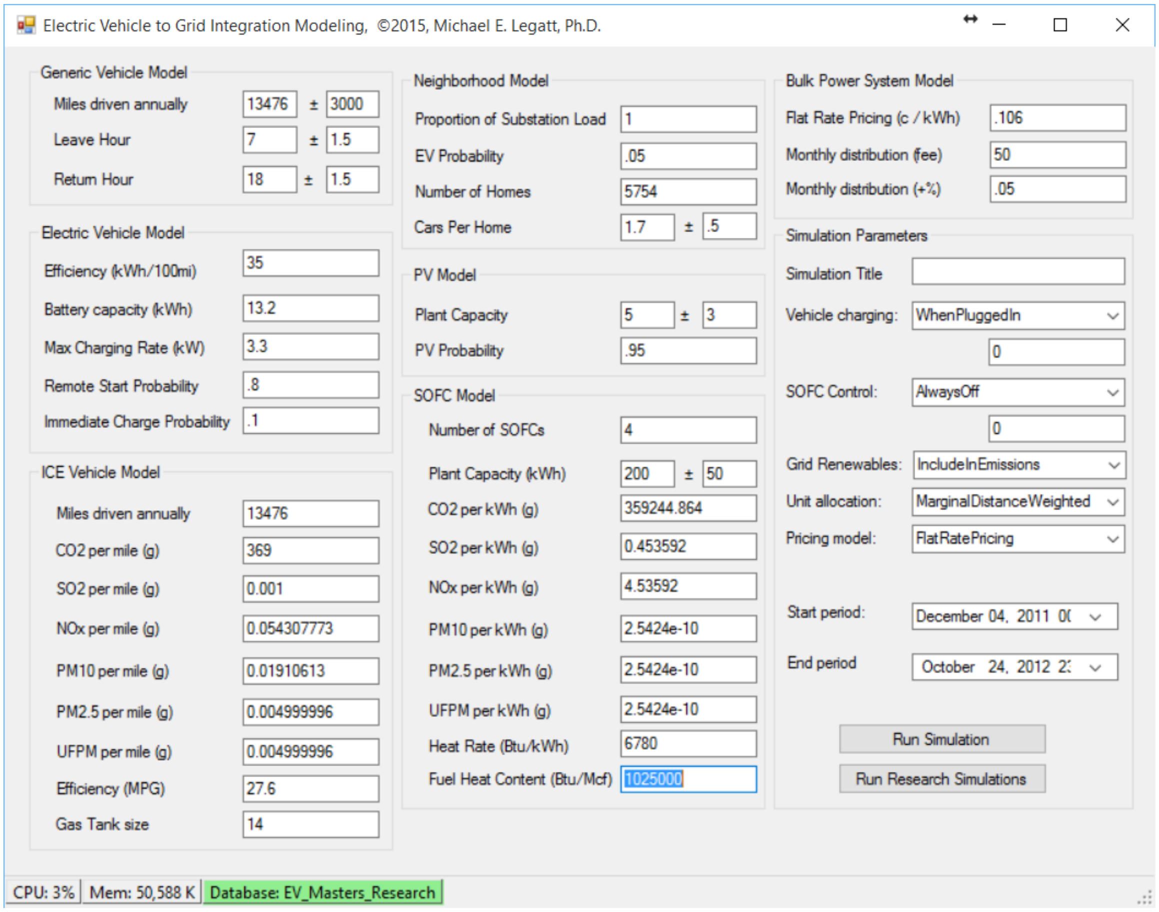

Figure 15: Simulation configuration UI for the EV to Grid Integration simulation

Vehicle models

The generic vehicle model includes parameters for annual miles driven per vehicle (the current EIA average of 13,476 was used), and the mean and standard deviation of hours that the driver left and returned from home. The ICE vehicle model adds emissions (CO_2, SO_2, NO_X, PM_{10}, $PM_{2.5}$, and UFPM) in grams per mile, vehicle efficiency, fuel tank size, and historic gas price data for the simulated neighborhood. The vehicle parameters were based on the 2014 Honda Civic averages as provided by the EPA, and assumed values for PM2.5 and UFPM, as no authoritative values were located. The electric vehicle model adds vehicle efficiency, battery capacity, maximum charging rate, and probabilities for a remote start (pre-conditioning the batteries and cabin prior to leaving for work or home), and for an immediate charging session start, as opposed to delayed charging. These parameters were based on the 2011 Chevrolet Volt.

Neighborhood models

The neighborhood model contains a scaling factor as compared to a particular substation's load, the probability that a selected vehicle would be a plug-in electric vehicle, the number of homes in the neighborhood, the distribution of vehicles per home, and the historic ambient weather data for the region. While running, the simulation system takes the load and its estimated associated emissions at the specified transmission level, and scales them to the neighborhood level.

Given the expectation of a fairly dynamic system, including new generators coming online, modifications to scrubbing technologies at existing power plants, and changes since the build-out of the CREZ system, and in order to align with the author's home PV system, a range of data were selected from December 2011 to October 2012.

Agent-based Energy Modeling

PURPOSE

In order to create models of neighborhoods with differing numbers of homes, load, distributed generation, ICE vehicles, electric vehicles and microgrids, an agent-based modeling system was developed. Due to the expectations that a variety of factors could influence a neighborhood's load and distributed generation, a small neighborhood was simulated, rather than a city or state-level agent modeling. The inputs to this model include selection of a transmission-level load, assigned to serve the neighborhood (which could include a scaling factor for the neighborhood against the total of the transmission-level load), 15-minute telemetry from a PV inverter, SCED data for marginal unit determination, LMP costs at the transmission bus, AMPD hourly emissions data, and overall systems data scaled on a per-MWh level to the neighborhood. When possible, available real-world data are provided in mean and standard deviation, and individual values are determined randomly based on a Gaussian distribution with this mean and standard deviation.

Neighborhood and home assumptions

The Northwest Hills area of Austin, Texas is located near several major highways including MoPac, 183 and Loop 360. Its center is approximately 1.5 miles away from the Austin Energy Steck substation, which also contains three electrical buses (STECK, STECKY, and STECKZ), on which locational marginal prices are computed every five minutes. For purposes of economic analysis, the STECK LMP (and its corresponding single load) was chosen as a benchmark LMP, and presumed to provide a representative sample of a residential load.

During the time range in question, the substation transformer saw loads between 3.1 and 28.77 MW, averaging 8.39 ± 3.40 MW. Interestingly, as shown in Figure 16, the load tended to peak during the winter months, even more so than the summer months, a likely indicator of electric heating systems being the most active loads in the winter. This neighborhood was modeled to include 5,754 homes, based on the assumption that 1 MW of load on peak translates to approximately 200 homes, as is often quoted in news media in Texas.

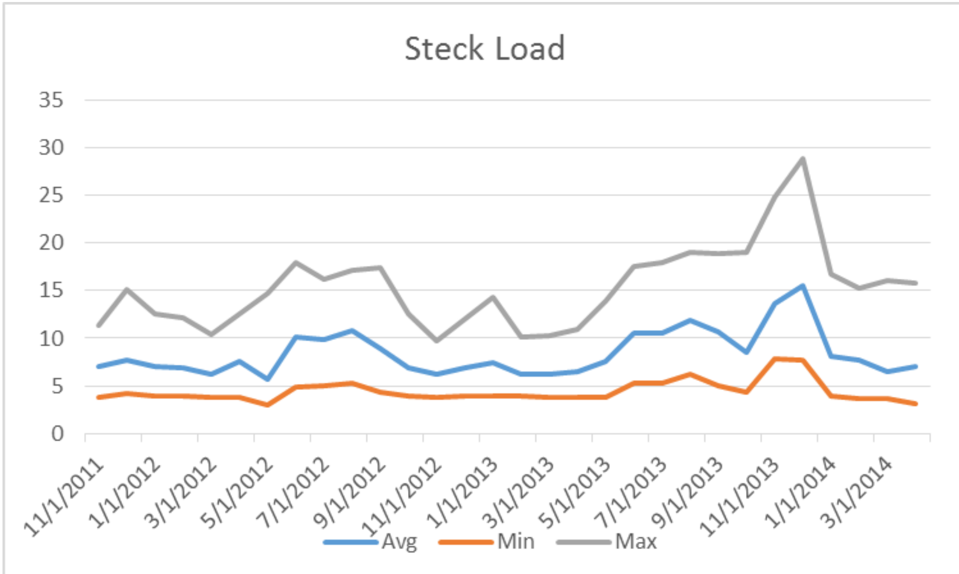

Figure 16: Monthly analysis of a load in the STECK substation

Transmission-Level generation assumptions

Emissions from transmission level resources were generated from the EPA CEMS data, and prices from LMP data. The simulation engine can be configured to perform four different types of analyses to determine which generators serve the neighborhood's load. These per-unit load numbers are used to determine emissions levels. For those that are based on a unit being marginal, the marginality is identified by a unit's SCED base point being greater than its low dispatch limit (LDL) and less than its high dispatch limit (HDL).

- Average weighting (All online units share equal proportionality of generation).
- Marginal average weighting (All marginal units share equal proportionality of generation)

- Marginal distance weighting (Each marginal unit's generation is determined by the weighted distance between the unit and the load, based on direct distance). This is defined by $w = \frac{\sum_{i=0}^{n} D_i - D_x}{\sum_{i=0}^{n} D_i - (n-1)}$
- Marginal shift-factors weighting. This approach utilizes shift factor data (often termed power transfer distribution factors, which show the linearized impact of power transfer between buses), if available, to determine the sources of changes in each unit's generation based on a modulation of load at a sink bus. Unfortunately, holistic shift factor data were not available for this thesis, although the application is configured for future work to be able to perform this analysis. Of the four approaches, this one is seen as the most accurate. The generation change can be computed as $R^{-1}*L_1$, where R^{-1} is a matrix with values of 1 across the first row, and subsequent rows with the shift factor N*N matrix where N is the number of marginal generators, and L_1 is a column vector with a 1 in its first entry, and 0 elsewhere.

Vehicle assumptions

These homes are assumed to have the 2010-average 1.7 vehicles per home, and thus roughly 9,781 vehicles in the neighborhood. This is likely an underestimation to Austin's overall averages (Musti & Kockelman, 2011). If each of these vehicles were to travel the 2014-average 13,476 miles per year, that would translate to 131,808,756 miles driven annually. If all these vehicles were ICE engines, the total emissions would include 53,614 tons of CO_2 (presuming 369 g CO_2/mile), 15,781 pounds of NO_x (presuming .054 g NO_X/mile), 5,521 pounds of PM_{10} (presuming .019 g PM_{10}/mile), and 2,905 pounds of $PM_{2.5}$ + UFPM (presuming .01 g $PM_{2.5}$ +UFPM/mile). With an average vehicle efficiency of 27.6 MPG, and average fuel price of \$3.40/gallon, this would translate to an annual neighborhood expenditure of \$16,237,311.

While it is the case that homeowners' vehicles in this region will travel outside it, due to the region's proximity to several highways and its shopping centers, it is likely that more vehicle miles and local air quality degradation occur than are reflected by the property owner-only model. However, one can also assume that drivers leaving the neighborhood for work may be partly offset by drivers coming into the area.

Photovoltaic generation assumptions

PV data was collected for a single home in the Northwest Hills Austin area between December 3, 2011, and April 16, 2015. This installation is comprised of seventeen 260-watt PV panels at a 209° azimuth, 24° tilt (fixed). During the time range, this 4.42kW installation produced a total of 17,009 kWh, with a peak generation of 3.895 kW. The distributed PV model presumes a 95% probability that a home will have a PV array, sized at 5 ± 3 kW. For homes with PV panels, their generation profile was presumed to follow proportionately with the historic data collected from the single home.

Driving Model

Both electric and ICE vehicles were analyzed in the model, and several common behaviors are observed between the two. Drivers are presumed to leave for work according to a Gaussian distribution (7 AM ± 1.5 hours), and return home according to another Gaussian (6 PM ± 1.5 hours). The two Gaussian random variables are assumed to be independent.

ICE Vehicle Model

In 2014, the average car fuel economy reached 27.6 mpg, and emitted an average of 369 g/mile CO_2 (Environmental Protection Agency, 2014). Therefore, this average vehicle at the annual average miles travelled of 13,476, would use 488.3 gallons of fuel and produce 10,963 pounds of CO_2. Using the AFLEET tool (Argonne National Laboratory, 2013), this vehicle would also be expected to emit 34.9 pounds of carbon monoxide, 1.6 pounds of nitrous oxides, 0.6 pounds of PM_{10} (including particles generated by disc breaking), 0.1 pounds of $PM_{2.5}$, and 0.1 pounds of volatile organic compounds. It should be noted that, for both hybrid and electric vehicles, the probabilities of the particles due to breaking would be significantly less, as those vehicles leverage regenerative breaking technologies.

The vehicles are presumed to have gasoline tank capacities of 14 gallons, and drivers are expected to fuel their vehicles when their tanks have less than 2 gallons remaining. Based on the modeling, this includes the assumption that their fueling will either occur after leaving home, or before returning. In order to track the associated emissions with refueling their vehicles, the model tracks gallons of fuel pumped for each hour (en route to work or home), and relates emissions based on ambient historic temperature in the neighborhood. During this analysis, the impact of smog contributions associated with ICE refueling during sunlight hours was not included, and thus may be included in future works.

Electric Vehicle Model

The electric vehicle model is based on the Chevrolet Volt, including a maximum usable capacity of 13.2 kWh, and a maximum charging rate of 3.3kW. Drivers are expected, on occasion, to remote start their vehicles (pre-cool or pre-heat the cabin), and are expected at some probability to being charging immediately when they return home, as opposed to doing a delayed-start charging, or allowing the neighborhood energy management system to control the vehicle.

Emissions rationale: Vehicle electrification

At a high level, using national averages for coal and natural gas CO_2 emissions, and assuming an electric vehicle efficiency of 35 kWh/100mi, it becomes clear that an electric vehicle may be lead to somewhat lower emissions of CO_2 than from a tailpipe of an average vehicle, but that the transition to natural gas, overall mixed fleets or SOFCs yield far more significant reductions in emissions.

Combining EIA data on pounds CO_2 per kWh for coal and natural gas, and the proportions of coal (averaged across bituminous, sub-bituminous, and lignite) and natural gas (EIA, 2015), against 2014 average and capacity generation proportions for the ERCOT region (ERCOT, 2015), the emissions savings from the grid's fuel mix sources become clear.

Emissions source	lb CO_2	lb CO_2 / kWh	% Reductions
Tailpipe	10,963		0%
Lignite coal	10,235	2.17	7%
Sub-bituminous coal	10,141	2.15	8%
Bituminous coal coal	9,763	2.07	11%
ERCOT grid by 2014 average generation	5,962	1.26	46%
Natural gas	5,707	1.21	48%
ERCOT grid by 2014 capacity	5,550	1.18	49%
Renewables	0	0.00	100%
Nuclear	0	0.00	100%

Table 2: Estimated annual CO_2 emissions from tailpipe and electric power generation (EIA, 2015)

However, the emissions associated with vehicle charging do not simply reflect proportions of emissions from annual average fuel sources. Renewables, both at the distribution and transmission level, play significant roles in determining the average systems emissions per kW, and often system dynamics are even more complex. Adding or removing an extra kW of load on the system could be thought of as changing one or more marginal generators. On-peak, this would likely be peaking units that would need to change their output in order to maintain the system balance between generation and load. Or, one could think of that kW, if controlled, as coming on- or offline in response to a corresponding change of kW at an intermittent renewable. If that were the case, then the emissions associated with that change should be virtually zero, as the marginal system change is captured by our controlled vehicle.

MODEL LIMITATIONS

While models exist for wheels-to-wells analysis, such as Argonne's GREET model, the purpose of this model is to provide a different view of the ERCOT region, to analyze permutations of complete and partial integration of vehicles and renewables with the bulk power system. There are externalities of both financial and environmental output costs not included in this model, such as the emissions associated with the manufacture of ICE and electric vehicles, the upfront cost of EV or ICE vehicle purchase, the emissions costs associated with gasoline fueling stations (at which smog-forming emissions are particularly affected by sunlight), airflow modeling of SO_2, NO_X and PM, and so forth. The purpose is to produce an initial feasibility assessment that is hoped will lead to more complex models and more detailed experiments.

In addition, the transition to a community microgrid includes a great deal of additional costs, from property space, natural gas pipelining, fuel costs, emissions monitoring equipment, SCADA equipment, and so forth. Again, the purpose is to determine more of a ceiling on emissions associated with the combined electric power/light vehicle transportation sectors.

Furthermore, due to limitations in data availability, a hybrid approach of marginal emissions was taken, first by determining the marginal generating units by their SCED basepoints lying between their low and high dispatch limits (which is not entirely accurate, as a unit could be marginal and at either edge, but only able to move in one direction). Furthermore, as the constellation of shift factors was not readily available, critical constraint-associated factors were included, while others were inferred by the total transmission line distance between the load substation and its shortest path to particular units.

When possible, state estimated data were used for analysis, as opposed to four-second SCADA telemetry. While this decision reduced the temporal resolution of the input signals (e.g., unit MW output), state estimation was seen as producing more overall consistent signaling across all the devices and device types in the system.

Algorithmic Analysis

Analysis of a particular point in time is conducted using a series of linear steps with some controllable parameters, with primary inputs from ERCOT, CEMS, fuel cost, weather, and agent behaviors. After all the data are integrated for that hour period, and unit information are integrated between ERCOT state estimated (physical-unit based), LFC (logical-unit based), and CEMS (physical-unit based with different nomenclature), the selection process continues. The following steps are undertaken to construct the point in time. All stochastic parameters are determined using a mean and standard deviation input against a Gaussian curve to produce a random number.

1) Computing the state of each electric vehicle: whether traveling from home to work, work to home, or remaining at its current location, based on the departure times.
    a. If the EV undergoes transit (for simplicity's sake, all transportation is presumed to take place within one hour), the driver may opt for a brief remote start session, to thermally condition the cabin and/or battery pack
    b. If the EV undergoes transit and then plugs in, and is either on an average-rate charging model, or average-rate peak-avoiding charging model, the set charge rate per hour is determined at this point. In the average-rate charging model, the EV charge rate is set to the total needed charge over the anticipated charging period (battery capacity – current state of charge)/hours of charging. In the peak-avoiding charging model, the hours of charging include only hours that are not on-peak, and the vehicles will only charge during those hours (Kefayati, 2014).
2) Computing the state of each ICE vehicle: whether traveling from home to work, work to home, or remaining on its location, based on the departure times.
    a. If the vehicle is traveling, its emissions are computed and aggregated.
    b. If the vehicle's gasoline tank, upon arrival, has less than two gallons, the costs of a full refueling are added.
3) Computing grid-level uncontrolled intermittent renewables.
4) Computing the transmission-level prices at the sink electrical bus.
5) Computing the uncontrolled distributed energy resources, by determining the PV generation on each roof.
6) Computing the total system-wide fossil fuel-associated emissions from electric power generation.

7) Determining whether each electric vehicle is charging, depending on its mode:
    a. If the charging mode is average-rate or average-rate peak-avoiding, charge at the previously computed rate.
    b. If the charging rate is based on emissions, avoid charging when the grid's overall CO_2 footprint is greater than a certain rate.
    c. If the charging mode is based on prices, avoid charging when the sink electrical bus' LMP exceeds a set value.
    d. If the charging mode is designed to avoid on-peak charging, charge at full when off-peak, and not at all on-peak.
    e. If the charging mode is designed to offset the distributed solar, charge all vehicles up to the level of the total neighborhood PV generation.
    f. If the charging mode is designed to offset the grid-level wind, charge all vehicles up to the level of grid wind generation.
    g. If the charging mode is designed to offset distributed and grid-level renewables, charge all vehicles up to the level of the combined renewable generation.
    h. If the charging mode is designed to offset all non-emitting generation sources, charge all vehicles up to the level of those resources (grid-level wind, grid-level solar, distributed energy resources, nuclear power generation, and hydroelectric power generation). Note that for the steamer components on combined cycle units are not included in this analysis.
8) Computing the behavior of the solid oxide fuel cell (SOFC) generation:
    a. If the SOFC is set to always run, generate the maximum capacity of the unit.

b. If the SOFC is set to offset solar, generate the difference between the maximum capacity of the distributed PV panels and their current total generation.
c. If the SOFC is set to offset vehicle charging, generate as much as possible to compensate for the electric vehicle charging behavior.
d. If the SOFC is set to generate when the PRC falls below a certain level, and thus generation supports reliability, then the unit will follow accordingly.
e. If the SOFC is set to generate when the LMP at the sink electrical bus rises above a certain level, the unit will follow accordingly.

9) Computing the marginal units that serve the remainder of our load, by determining all units that have a basepoint in between, but not equal to, the unit's HDL and LDL values.
10) Determining the prices and emissions that are associated with the load not served by the distributed resources or SOFCs:
    a. Average grid rate determines the prices and emissions based on all the average per-MW prices and emissions across all online emissions-generating plants, multiplied by the neighborhood load.
    b. Marginal average determines the prices and emissions based on the average per-MW prices and emissions across all emissions-generating marginal units, multiplied by the neighborhood load
    c. Marginal distance weighted determines the prices and emissions based on the weighted average of prices and emissions across all emissions-generating marginal units and their straight-line distances to the sink electrical bus, multiplied by the neighborhood load.

d. Shift factor-weighted determines prices and emissions based on a matrix computation between all marginal units and the sink bus, using the following components:
    i. C – The row vector of prices corresponding to the marginal generators (1 x N)
    ii. E – The row vector of emissions corresponding to the marginal generators (1 x N)
    iii. R – An inverse of a matrix whose first row is all 1s, and subsequent rows correspond to a sub-matrix with columns of changes in output, and rows of the binding constraints (N x N)
    iv. L1 – A column vector with its first entry as 1, 0s elsewhere (N x 1)
    v. The total cost of the generation change is defined as C * R * L1
    vi. The total emissions associated with the generation change are defined as E * R * L1.

11) Determining the remaining total plugged-in EV battery capacity and state of charge, as well as the total gasoline capacity and storage within the neighborhood.

ASSUMPTIONS

A great many parameters for the Texas bulk power system were unavailable. While most fossil fuel facilities reported hourly gross MW emissions, and rates and total weights of CO_2, SO_2, and NO_X, no such information was easily available for PM_{10}, $PM_{2.5}$, and UFPM. Therefore, the most specific proxy for emissions locatable was the EPA Emissions inventory, which includes particulates and NOx, and are downloadable by county. Thus, plant emissions are assumed to follow a similar ratio to NOx, and thus are inferred from them. As the EPA emissions monitoring equipment classifies all equipment at 2.5μm or smaller as $PM_{2.5}$, those numbers are split 50% between $PM_{2.5}$ and UFPM.

Unfortunately, shift factor data were not easily locatable at the necessary level of granularity within the time scope of this research. As such, while the code base is able to handle a matrix of shift factors, none were easily available. Thus, average and location-based rates were used for purposes of this research.

Analysis Factors

In order to provide sufficient means for analysis, 346 permutations of the neighborhood simulation were conducted. These included the following parameters:

- Sensitivity analysis of uncontrolled EV and PV adoption
    - Probability of a home having an EV, 5%, 50%, 75%, and 95%
    - Probability of a home having PV panels, of 5 ± 3 kW capacity, 5%, 50%, 75%, and 95%
- Integrated neighborhood management analysis.
    - Number of SOFCs: 5, 25, 50, 100, and 143. Each of these are based on the Bloom Energy SOFC, generating at 200 kW ± 50 kW. The upper value of 143 was determined as a proxy for the full generation capacity being able to support the neighborhood's historic summer load, although this certainly would lead to extreme levels of over generation in many circumstances.
- Vehicle charging styles: The following vehicle charging styles were computed:
    - When plugged in – all vehicles start charging immediately upon plug-in

- Defer to off-peak – the vehicles will not charge (although may remote start) during on-peak hours, which are defined as between 8-10AM, and 5-8PM, inclusive.
- Average rate charging – at the time of plug-in, with departure hour estimated, the vehicle will charge at a fixed rate of its remaining charge divided by the number of hours, whether those hours are on-peak, off-peak, or mixed.
- Average rate charging off-peak – at the time of plug in, with departure hour estimated, the vehicle will charge at a fixed rate only during off-peak hours, at fixed rate of its remaining charge divided by the number of off-peak hours.
- Based on prices – When the spot market prices at the STECK load bus surpass a fixed value of $24/MWh, the vehicles will not charge.
- Follow DERs – Vehicles will distribute their charging such that the hourly sum of their charging has a maxima of the aggregated neighborhood PV generation.
- Follow grid renewables – Vehicles will distribute their charging such that the hourly sum of their charging has a maxima of the aggregated grid-level renewable generation, including wind and solar.
- Follow grid and distributed renewables – Vehicles will distribute their charging such that the hourly sum of their charging has a maxima of the combination of the grid-level and neighborhood-level renewable generation.

- Follow all zero emitting sources – Vehicles will distribute their charging such that the hourly sum of their charging has a maxima of the combination of all zero emissions-generating output, including neighborhood PV and SOFC, grid-level wind, solar, nuclear, and hydroelectric power generation.

- SOFC energization schedules: The following algorithms were used to determine whether an SOFC would generate during an hour. Some of the criteria handle offsetting other factors; as such, the total SOFC generation in those cases would equal the quantity to be offset. If no such parameters were specified, online SOFCs would each generate at their capacity.
    - Always off – Simulate the SOFCs being non-existent, never turning on
    - Always on – The SOFCs would run constantly
    - When price is above a certain level – The SOFCs would energize when the LMP at the STECK electrical bus surpasses a particular level
    - When PRC below a certain level – leverage the SOFCs to help provide additional capacity to the grid in situations where grid-level generators may have had forced outages, or other issues lead ERCOT to enter EEAs (energy emergency alerts). For this simulation, a PRC of 3,000 MW was used, so that the SOFCs could be thought of as an extra layer for grid security prior to the 2,500 MW levels that would lead to EEA generation
    - Offset vehicle charging – The SOFCs would be used to offset charging from the vehicles, so that the hourly rate of EV charging

would be compensated for by the SOFCs. One could think of this approach as utilizing the SOFCs (and their natural gas fuel source) as being linked to the vehicle.

- Offset solar – The SOFCs would be used to maintain a constant level of generation in the neighborhood, so should all PVs generate at their nameplate capacity, the SOFCs would be off, and otherwise, the SOFCs would make up the difference.

CHAPTER 4: RESULTS

Analysis of the data included validation of the existing ERCOT and EPA data, validation of the algorithmic function of the application, development of a base case scenario, and comparisons between different simulation parameters to determine maximization of emissions and/or cost reductions. This chapter includes an overall analysis of the base case scenario and tests of differing levels of EV and PV adoption across the base case. It further looks for scenarios that optimize for a particular outcome, such as lowest total CO_2, SO_X, or UFPM. It further investigates a theoretical but likely difficult scenario, in which the neighborhood attempts to maximize its generation resources, both across distributed renewables and solid oxide fuel cells.

SUMMARY OF DATA

A total of 346 cases were generated and analyzed, to determine means of minimizing cost, environmental impact, and threats to reliability. All further cases analyzed herein are compared to a basecase that attempted to capture a neighborhood with light rooftop photovoltaics and light electric vehicle adoption (both at 5%).

BASE CASE ANALYSIS: LIGHT SOLAR AND EV ADOPTION

In this basecase model, approximately 5% of homes had a PV array, and 5% an electric vehicle. From the transportation perspective, the neighborhood performed as expected. For the gas vehicles, drivers paid a total of \$18.0M to refuel their vehicles, which translated to \$0.126 per mile driven. The few electric vehicle drivers paid \$294.4k to charge their EVs, which translated to \$0.039 per mile driven. The neighborhood paid a combined \$6.8 M for their electric power (which included EV charging). From this perspective, a home would tend to spend 2.5 times as much for fueling their vehicles as it would for home energy.

Base case analysis

% miles EV driven	5%
Largest home load (kW)	17,883
Largest EV charging load (kW)	1,801
Cost reductions	69%
CO_2 reductions	80%
SO_2 reductions	128x growth
NO_X reductions	41%
PM_{10} reductions	73%
$PM_{2.5}$ reductions	62%
UFPM reductions	62%

Table 3: Analysis of cost and emissions changes in the base case scenario

During this time period, the grid generation totaled 30.7M pounds of CO_2, while the ICE vehicles emitted a total of 116.9M pounds of CO_2. This translated to 0.81 pounds of CO_2 per mile driven ICE, and 0.16 pounds per mile driven EV, or an 80% reduction in per-mile emissions for EV driving, based on the emissions factors of the marginal units that would serve the increased vehicle charging load. The grid generation during this time period totaled 52k pounds of SO_2, while the ICE vehicles emitted 317 pounds. On a per-mile basis, however, ICE SO_2 emissions were quite small (at $2.2 * 10^{-6}$ pounds), while per-mile EV emissions were significantly higher (at $2.8 * 10^{-4}$ pounds), over a hundredfold increase in SO_2 emissions. This pattern of increased SO_2 emissions per-mile been noted in several studies; e.g., (Meehan, 2013). Per-mile emissions reductions were found for NO_X (41%), PM10 (73%), PM2.5 (62%) and UFPM (62%).

From the generation perspective, DER generation tended to be fairly light, totaling 1.7GWh over the course of the time period. As there were no SOFCs online during this simulation, the remaining 65.3 GW load was served primarily by fossil fuel sources. The patterns of behavior of winter load tended to follow an electric-heat pattern, with grid-level wind tending to offset night load.

From the cost and emissions perspective, the electric vehicle drivers in this neighborhood enjoyed significant cost savings, and also produced 80% less CO_2 per mile driven than their ICE counterparts (0.478 lb/mi EV, 0.814 lb/mi ICE). These drivers, presumed to have their vehicles initiate charging on arrival at home or work did not produce any significant effects on the system, and there were no instances of their vehicles being insufficiently charged for their travel. EV drivers also likely did not impact the distribution system significantly, as the combined instantaneous peak load by their charging was 1.8MW, roughly an additional 10% over the peak home loads of 17.9MW, although this additional peak was not coincident with the peak home loads. Figures 16 and 17 highlight the load (orange) and total CO_2 emissions (blue) over the course of a winter and summer month, respectively. The behavior of grid-level renewables and shifting proportions of base load and peaking units, and coal and gas units, tended to change the total CO_2 emissions per MW over time.

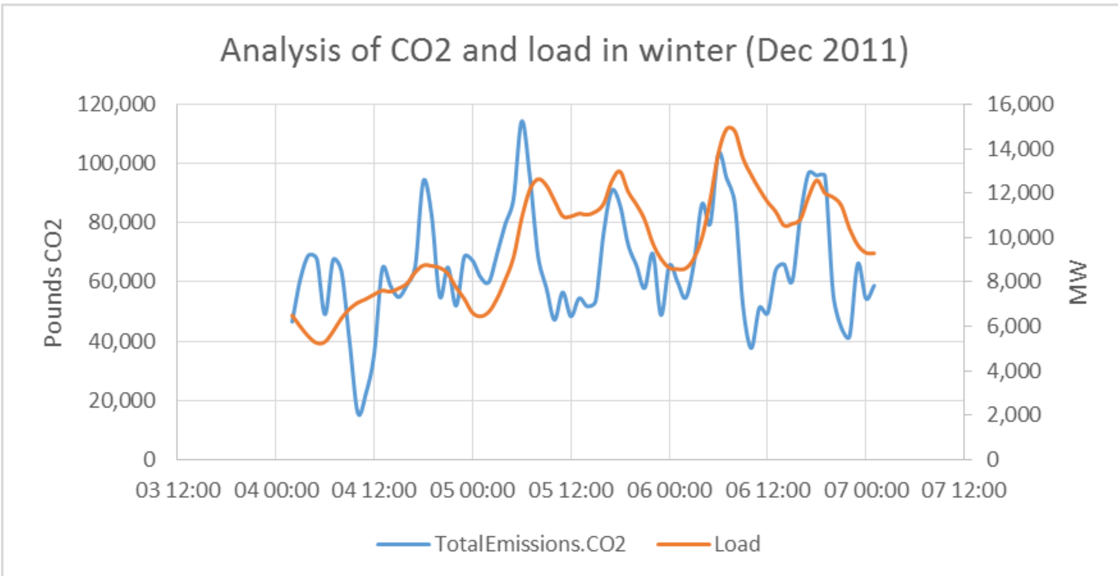

Figure 17: Neighborhood load during a winter period

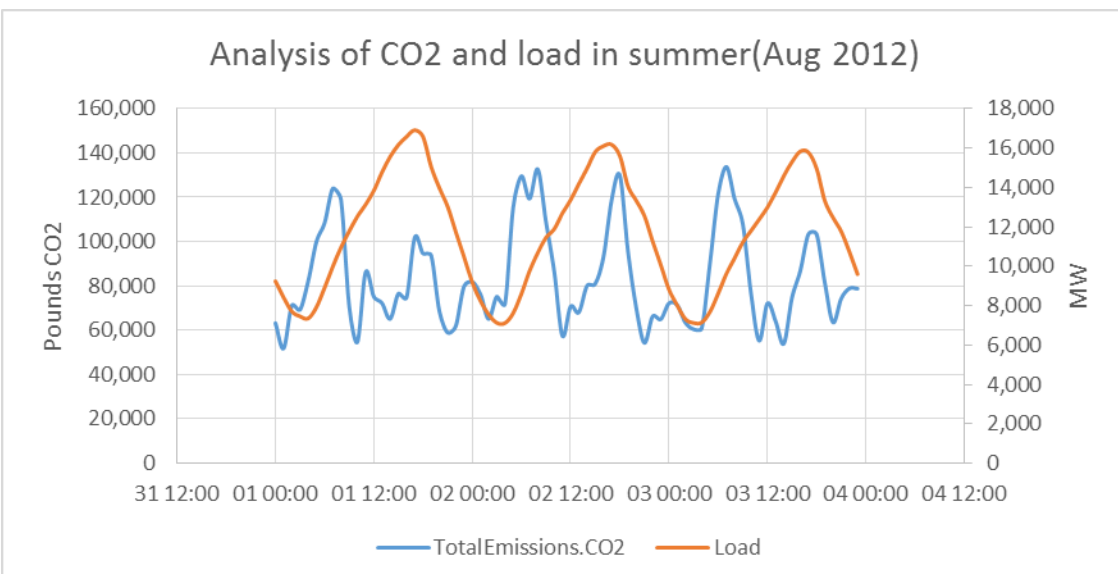

Figure 18: Neighborhood load during a summer period

Lowest emissions per mile

If one were to focus on lowering CO_2 emissions through the combination of electric vehicles and other technologies, one could take two approaches. First, looking at simply reducing or eliminating the per-mile emissions would be one approach. As expected, this required two activities: high adoption rates of distributed renewables, and vehicle charging strategies associated with renewable integration. When the vehicle controllers were set to charge to follow grid-level wind, or distribution level solar, they could be thought of as effectively having zero emissions, simulating a scenario in which the vehicles were dynamically following a renewable resource. Other strategies, however, produced nearly identical results with large PV adoption rates, and average rate charging behaviors. In these models, PV adoption rates were so high, that charging during peak hours still led to minimal need for grid-level generation, as conceptually, the distributed photovoltaics were offsetting the homes' largest mid-day loads associated with heating and cooling. From an implementation standpoint, average-rate charging (either on- and off-peak or off-peak) is a far simpler algorithm to employ, and requires no dynamic controller in the control loop, whereas other strategies such as following distributed or grid level renewables, require a system to integrate information and provide control signals to the vehicles. In order to achieve further reliability-enhancing services, such as response to PRC, local frequency, or to offer ancillary services, a controller would likely be a required in the loop, especially in order to ensure that a large fleet of vehicles does not simultaneously change behavior or cause oscillations.

LOWEST OVERALL NEIGHBORHOOD EMISSIONS

Interestingly, the overall neighborhood emissions analysis tends to look quite similar to that of the lowest emissions per-mile, with a caveat. From the CO_2 perspective, given the significant reductions observed with EVs, to achieve a significant reduction, a neighborhood needed both 95% adoption of electric vehicles and photovoltaics, and SOFCs were of limited benefit. With that in place, the charging schemes tended to be less relevant to overall emissions reductions. Of course, in a real-world sense, significant PV generation during light load periods (e.g., the middle of a mild day) would lead to other reliability concerns, in which case charge management techniques may be more valuable.

If the goal were to reduce SO_X emissions, a different approach needed to be taken. As the only cases to evaluate EV adoption rates were the basecase, the lowest SO_X emission case produced 32,123 pounds of SO_X, and was one in which the neighborhood had a 5% EV adoption rate, and a 95% PV adoption rate. Effectively, this used photovoltaics to offset what would have been grid-sourced fossil generation.

If reductions of NO_X were the goal, the same approach of high EV and PV adoptions combined with average rate and average rate off-peak were highly effective in generating lower NO_X levels. Like in SO_X, from the vehicle perspective, these patterns produced significant (roughly 5.5x growth) in per-mile EV vehicle emissions, yet this is more than compensated for by the reductions in neighborhood grid loading, and thus overall, produces the lowest emissions. As SOFC generation came online with the three schemes, infrequent generation that occurs only when PRC drops below a certain level led to a 7% increase in emissions, while schemes that grew SOFC generation also increased SO_X emissions. All of these levels, however, were significantly lower than the basecase, so all of these approaches led to reduced emissions compared to what likely actually occurred during the time period.

The combination of EV and PV charging led to significant reductions in particulate matter, whether PM10, PM2.5, and UFPM. From a sensitivity analysis standpoint, adding solar had somewhat less effect in reducing the PM2.5 emissions than did EV adoption, although both worked together to reduce the overall footprint.

Emission	CO_2		SO_X		NO_X		PM_{10}		$PM_{2.5}$		UFPM	
Adoption	**PV**	**EV**	**PV**	**EV**	**PV**	**EV**	**PV**	**EV**	**PV**	**EV**	**PV**	**EV**
Lowest value	44,362,469		32,123		17,779		2,992		2,992		1,046	
Lowest emitting	95%	95%	95%	5%	95%	95%	95%	95%	95%	95%	95%	95%
	75%	95%	75%	5%	95%	75%	75%	95%	75%	95%	75%	95%
	50%	95%	50%	5%	75%	95%	50%	95%	95%	75%	95%	75%
	5%	95%	95%	50%	95%	50%	95%	75%	50%	95%	50%	95%
	95%	75%	5%	5%	75%	75%	75%	75%	75%	75%	75%	75%
	75%	75%	75%	50%	50%	95%	5%	95%	95%	50%	95%	50%
	50%	75%	50%	50%	75%	50%	50%	75%	50%	75%	50%	75%
	5%	75%	95%	75%	50%	75%	95%	50%	5%	95%	5%	95%
	95%	50%	75%	75%	95%	5%	5%	75%	75%	50%	75%	50%
	75%	50%	95%	95%	50%	50%	75%	50%	5%	75%	5%	75%
	50%	50%	5%	50%	75%	5%	50%	50%	50%	50%	50%	50%
	5%	50%	50%	75%	5%	95%	5%	50%	95%	5%	95%	5%
	95%	5%	75%	95%	5%	75%	95%	5%	5%	50%	5%	50%
	75%	5%	50%	95%	50%	5%	75%	5%	75%	5%	75%	5%
	50%	5%	5%	75%	5%	50%	50%	5%	50%	5%	50%	5%
Highest emitting	5%	5%	5%	95%	5%	5%	5%	5%	5%	5%	5%	5%
Highest value	140,720,983		92,053		30,536		7,955		7,955		2,339	
Effective reduction	68%		65%		42%		62%		62%		55%	

Table 4: Basecase parameters for emissions reductions

Lowest UFPM emissions

Interestingly, based on the simulation parameters, UFPM emissions caused by the neighborhood tended to be far more stable, although there was a slight overall reduction in UFPM emissions by moving to vehicle electrification. Across all cases with a 95% EV adoption rate, between 13,139 and 13,146 pounds of UFPM were generated during the time range. By reducing the EV adoption rates to 75%, UFPM increased to 13,458 – 13,477 pounds, at 50% adoption, UFPM increased to 13,872 – 13,892, and at 5% adoption, UFPM increased to 14,626 – 14,644.

However, it should be noted that while the trend towards vehicle electrification does reduce UFPM in total, the increased distance between the UFPM emissions sources and neighborhood, combined with the inverse-square behavior of UFPM travel would mean that the local air quality and human health in this neighborhood would likely be significantly improved. It is the case, however, that this neighborhood would be just one of many served by a power plant. It should therefore also be considered what effect significant increases in UFPM emissions at power plant sites would have on nearby populations (based on their distances to the plants), and whether any other secondary effects would occur by consolidating UFPM to those sites.

LIGHT SOLAR ACROSS VARYING LEVELS OF EV ADOPTION

As expected, in a neighborhood with light PV adoption rates (5%), increasing EV adoption led to decreases in ICE miles driven (143.8M miles for the 5% EV adoption case, to 7.4M miles in the 95% case), and the EV miles driven complemented the difference. ICE fueling costs per mile were consistent at $0.126/mile, while the EV costs per mile varied greatly. As the adoption of electric vehicles went up, more energy needed to be purchased from the spot market, often served by marginal generators. This led to a cost per mile between $0.039 for the 5% adoption rates, up to $0.213 for the 95% adoption rates.

Fossil fuel use for generation nearly doubled as well, from 65.4GWh for the low EV adoption rate group, to 114.5GWh for the high adoption rate group. Given these simulation parameters were looking at marginal generation, this had the effect of excluding grid-level renewables, so these numbers could be thought of as a worst-case scenario. As expected, adding in additional load served by the bulk power system, particularly marginal peaking plans, produced increased emissions as well, and thus could be seen as a worst case scenario. While there were greater emissions (thus less reductions) as EV adoption rates increased, interestingly the primary change was in the cost per mile driven, which quickly became highly negative. Moving from 5% to 95% EV adoption in this scenario effectively reversed the effect size of the cost reductions (due to increased costs of greater on-peak charging), with ICE refueling at the same benefit that 95% adoption that EVs had at 5% adoption.

This type of adoption also produced a great many other concerns, including significant growth in EV charging loads, more than doubling the maximum instantaneous household load. This type of scenario, were it to occur, would likely lead to a host of problems, from generators exceeding EPA limits, large congestion on the system (and thus growth in pricing that was not incorporated in this model), EEA risk, and damage if not outright failure of distribution transformers. Clearly, this is not a desirable outcome. While a sensitivity analysis was not conducted by incrementing EV adoption rates, it is clear that at some point between the 5% and 50% rates of EV adoption, the cost of charging large numbers of electric vehicles, without additional local generation sources becomes not economically beneficial.

Light PV adoption analysis

PV Generation	5%	5%	5%	5%
% miles EV driven	5%	50%	75%	95%
Largest home load (kW)	18,117	25,364	32,054	39,153
Largest EV charging load (kW)	1,801	18,193	27,269	34,367
Cost reductions	69%	-29%	-55%	-70%
Per-mile CO_2 reductions	80%	80%	80%	80%
Per-mile SO_2 reductions	-128	-131	-131	-131
Per-mile NO_X reductions	41%	39%	39%	39%
Per-mile PM_{10} reductions	73%	72%	72%	72%
Per-mile $PM_{2.5}$ reductions	62%	61%	61%	61%
Per-mile UFPM reductions	62%	61%	61%	61%

Table 5: Light solar adoption across EV adoption rates

At the highest adoption rate, the vehicle-associated charging loads totaled 51.9GWh, nearly the same as the homes' non-vehicle total load of 62.8GWh, effectively doubling the size of the neighborhood's load. If one were to imagine this scenario playing out with nearly every vehicle being electric and no distribution-side support from PV or SOFCs, it would likely mean significant risks for doubling of peaks, both in summer and winter. From the distribution perspective, SOFC generation might be useful to offset EV charging, but the distribution transformers at the home would still be a thermal overload risk with the combined EV charging and HVAC-associated loads during peak times.

"All-out Generation"

When analyzed, the scenarios with 143 SOFC generators (which, in theory, were designed to be able to fully handle the neighborhood load on peak), negative changes in emissions overall were noted during daylight hours, as the PV panels generated and SOFCs ran all the time, thus generating beyond the neighborhood's load and beginning to offset marginal generators. These cases were not considered as practical, as they violate the tenet of a distribution system largely acting as a sink, not a source for energy. Based on both the planning and management assumptions that are typically made in developing and maintaining the distribution system, and in modeling the transmission system, this change could produce new challenges. For example, the network model, market and settlement systems at the ISO level do not anticipate negative load, and questions about zonal load prices vs. nodal generation prices are ones not currently resolved. Furthermore, load resources are typically bid in based on a pause of load; in a world with negative load levels, there may be need for load resources to be dispatched to be energized.

A 100-SOFC (20 MW) generation system was able to, combined with large photovoltaic and EV adoption, lower emissions across the neighborhood. In this scheme, CO_2 emissions were reduced 68%, SO_X emissions grew by 37% (although other EV charging schemes were seen to be able to compensate for this), NO_X emissions were reduced by 42%, PM_{10} by 62%, and UFPM and PM2.5 by 55%.

While this strategy could be seen as reducing emissions significantly, the cost factors were of import as well. It would be worthwhile to investigate of a single 20MW CNG unit as opposed to several SOFCs. It is possible this approach could scale to a single device, likely take up less space, and potentially leverage additional emissions control systems to further reduce its emissions.

CHAPTER 5: DISCUSSION

Summary of key findings

Overall, this work shows that the combination of distributed photovoltaic generation, microgrid SOFC generation and vehicle electrification can produce significant reductions in overall emissions, and help to move UFPM emissions far away from a population center.

Across all emissions types, it appears that intelligent electric vehicle charging, combined with distributed renewable generation and microgrid generation, can produce significant reductions in emissions, and ongoing cost savings for both electric power and transportation. However, it also highlights the myriad of risks associated with stochastic driver behaviors, and the ways in which different control parameters for both SOFC generation and EV charging can lead to significantly different outcomes for costs, emissions, and the reliability of both the bulk power system.

In many ways, this is the traditional problem seen as we move to a world of increased efficiencies and technology: as technologies scale and become more dynamic and responsive, the tolerance ranges tend to shrink. Either the technology, whether a catalytic converter, neighborhood energy management system, or mobile phone battery management system, is in an ideal state (as measured by far better than unmanaged-average efficiencies), or it is not (typically far worse performing than unmanaged-average).

Therefore, the real-time communications between electric vehicles, homes, a neighborhood controller, and the bulk power system may be a requirement for this next level of efficiency and growth. This also certainly echoes Presidential Policy Directive 21, which highlights the energy and communications sectors as particularly critical for all critical infrastructures, because of the enabling roles they play for all other critical sectors. This kind of dynamic system, if implemented, would rely heavily on the communications sector in order to maintain the health of the neighborhood's energy operations. One could also imagine this system gaining additional economies of scale by providing CHP to a neighborhood, and in interfacing with the water and natural gas pipeline infrastructures, thus benefiting from additional strong links to those controllers.

There are a great many reasons society may want to consider growth in distributed and grid-level renewable energies. Aside from a high upfront cost, renewable generation systems tend to have a fairly low cost for maintenance, with no ongoing fuel costs. However, their intermittencies pose a problem to both distribution and bulk electric reliability. Certainly, in areas like California and Hawaii, fears of DER overgeneration are seen as a risk, because they could so significantly offset the grid load, that fossil fuel plants would have to go offline, in order to avoid dropping below their low sustainable limits.

From the ISO perspective, these intermittent generation sources pose additional challenges to those tasked with ensuring the reliability of the system. Sometimes, unanticipated ramps could occur in between state estimation and contingency analysis runs. This would mean that traditionally slow-moving data could change at a far more rapid pace, leading operators to have, either due to their memories or the differential rates of systems updating, incorrect assumptions about the state of the system.

Historically, the mental model of grid operations was straightforward: one had a fleet of controllable generation that could reliably be dispatched. One also had a large, partially predictable (largely associated with time of day), partially stochastic (largely associated with weather), and anonymous collection of users whose loads needed to be served by those controllable generators. Furthermore, the operators had some reasonable tools to predict the aggregate behavior of those users, based on very few factors. The grid operator's job was also more simple, to maintain frequency, voltage, to avoid any real-time thermal or voltage violations, and to keep meeting the demand of the loads continuously.

In the past decade, this paradigm has shifted tremendously. Grid operations has continued to move towards a contingency (N-1) reliability model, rather than a basecase reliability model. New factors need to be considered and risks averted, such as subsynchronous oscillations, cyber-attacks, geomagnetically induced currents, electromagnetic pulses, and recovery mode preparations such as black start. In real-time operations, grid operators have to contend with changes in controllable generation, such as shifting fuel sources, which leads to somewhat different mental models of plant function. In Texas, the increased adoption of natural gas as a fossil fuel source also implies increased interdependency between the energy and natural gas sectors.

Furthermore, intermittent generation resources began to come online, first with a consistent set of behaviors, such as large West Texas wind farms behaving in one fashion, then later with Coastal Texas wind farms tending to behave somewhat differently. Now, as grid-tied solar is growing, operators will need to build additional mental models to understand, anticipate, and comprehend these new generators, in order to maintain a high level of situational awareness.

One of the interesting facets of this research is due to the fact that while electric vehicles are not a new concept, in this consumer market, the 2011 Volt and Leaf are considered the first mainstream EVs to have entered the public consciousness. Therefore, these new devices are disrupting our pre-existing habits (such as traveling often to the gas station), and offering society the potential to build a series of new habits.

If these habits included participating in an EV charging controller/aggregator system, then the grid operations story could be changed powerfully. In areas where "duck curve" concerns are significant, large numbers of EV charging sessions could be controlled onto those time ranges, effectively offsetting the renewable generation. From an intentionality standpoint, this could also be seen (as this research does) of near-completely eliminating the emissions associated with vehicle charging and driving. If battery technologies continue to scale, this also means that residential energy storage devices have the capability of peak-shaving, or any other number of activities (including, potentially, simply storing energy for the EVs to use when they get home).

Therefore, in aggregate, control of major load devices such as electric vehicle charging offers a significant benefit to reliability operations. If these devices loads were controlled in reaction to intermittent generation, then the grid operator's function can be seen as moving somewhat back towards its prior, and more easily comprehensible modality: predicting uncontrollable system load, and moving controllable generation assets to meet the demand in a reliable fashion. Of course, there would still be other issues such as congestion management associated with residential/workplace EV charging in Central Texas offsetting wind and solar spread throughout the state. The only way to avoid this issue would be to "double down" on rooftop solar, and utilize neighborhood microgrids to help neighborhoods provide more consistent load profiles, and also be able to dynamically adjust to co-optimize the grid and neighborhood's electric reliability. If one also adds in constraints on distribution transformer and line thermal issues and cool-down periods, then rooftop solar, and potentially residential energy storage, would be needed to maintain the life of those devices.

Future work

This work suggests several different avenues that would benefit from further analysis. This tool has shown the power of controlled electric vehicle charging and microgrid generation to save in energy costs, and to significantly reduce environmental impacts. However, further analyses are needed from the economic perspective, to determine the costs the additional infrastructure needed to support both the SOFCs and the aggregator/microgrid controller, as well as a detailed analysis of the gas pipeline infrastructure. Certainly, many costs of provisioning, permitting, and building a microgrid SOFC area are likely not inexpensive. Future analysis should also look at additional scaling benefits, such as using CHP, potentially providing neighborhoods with hot water and HVAC functionality. Just as is the case with transportation fuel sources, scaling these technologies (and presuming robust pipelines to transmit cold and hot water without significant losses) can produce significant economies of scale and efficiencies.

Given the growing interconnectivity between electric power and natural gas (both in terms of growth of natural gas power plants, and natural gas compression stations using electric power), the future of the bulk power system will likely need a robust communications pipeline with the natural gas sector. Such issues are noted but outside the scope of this current project. The natural gas prices utilized during this analysis were based on the EIA spot market prices for natural gas; most likely these are not the most accurate pricing sources available. Furthermore, if the natural gas world is operating on a flat rate structure like electricity, it would be further of interest to analyze what time-of-use or congestion-based pricing might look like on the natural gas side. Already, as natural gas serves several critical roles, trade-offs need to be analyzed a priori. For example, in extreme cold weather, there is increased demand for CNG from homes with gas heating, but there is also increased demand for CNG from power plants that serve homes with electric heating. If one were to further add SOFCs with combined functionality, it may lead to the need for further analysis of the prioritization of different infrastructure points in N-1 situations.

In order to better understand the sources of marginal emissions, incorporating shift factors will likely improve the accuracy of the study significantly. If one were to take the alternate approach of presuming a dynamic rather than marginal contribution, the analysis tool would need to be augmented to be able to process the entire ERCOT model, process four-second SCADA telemetry, and produce power flows and contingency analyses. Peak times are currently defined as 8-10AM and 5-8PM throughout the year, although in practicality, a summer peak in the afternoon, and a diurnal winter peak would better reflect historic load profiles in Texas. Also, one could imagine using either an absolute MW value, or PRC value as a proxy to peak generation, so that the computations are made based more on real-time system conditions.

From the generation side, marginal unit detection can be further enhanced, so that no unit is ramped above its HDL, or below its LDL. One of the charging parameters further considered was avoiding charging when the grid or neighborhood's overall CO_2 or UFPM footprints exceeded certain values, although this was not implemented because it was the least realistic; real-time emissions monitoring is not currently transmitted.

From the human side, several enhancements can be made to make the results a more reasonable measure. For example, drivers' driving patterns could be can be different between non-holiday weekdays and other days. When an ICE vehicle is refueled with the sun shining, especially with extreme temperature, additional contributions to smog are generated through the escaped gases. While it is the case that many new vehicles have technologies to capture the additional vapors emitted during fueling (and thus the EPA has suggested removal those requirements although it's estimated that 1/3 of vehicles on the road are not able to perform this function sufficiently (Sperry, 2012).

In order to support the existing distribution system infrastructure, and considering the continued cost decreases of lithium ion batteries (primarily due to economies of scale), future work should also simulate home energy storage devices, in a variety of configuration modes, such as supporting peak shaving, and storing PV generation to offset vehicle charging later in the day. While the software, as designed, can process shift factor matrices in order to determine the allocations of the neighborhood's loads across the marginal generators, this analysis would be more accurate if such data were available and integrated into the analysis.

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VITA

Michael E. Legatt is the principal human factors engineer for the Electric Reliability Council of Texas (ERCOT), which manages the flow of electricity to over 24 million Texas customers, about 90% of Texas' load. Dr. Legatt has been a programmer for over 20 years, and worked in the energy, financial, medical, neuroscience research and educational sectors.

He has a Ph.D. in clinical health psychology/neuropsychology from the Ferkauf Graduate School of Psychology/Albert Einstein College of Medicine, and is currently pursuing a Ph.D. in energy systems engineering at the University of Texas at Austin.

As an amateur (ham) radio operator, he received a commendation for helping to provide emergency communications during the 2003 blackout in the northeastern United States, which sparked his interest in the psychology of energy management. He works to build systems designed to provide operators with needed information, optimizing for perception, speed, comprehension, and stress management. He also works at the organizational level to support the growth of the industry's high reliability culture.

At ERCOT, his development of the Macomber Map® has been featured in the New York Times, National Public Radio, T&D World, and Forbes. The Macomber Map was credited as being instrumental in helping ERCOT operators maintain grid reliability during several record-setting wind generation levels since 2010, and through several severe weather events since 2009. Macomber Map is now freely available as an open-source application.

He also works on the behavioral aspects of consumer electric use, researching electric vehicle to grid integration, behavioral aspects of conservation and consumer awareness in grid management, and the cybersecurity, behavioral, and reliability issues that arise with integration of new technologies across layers of the grid. He is ERCOT's lead on a collaborative project with the University of Texas at Austin, EV-TEC and the Pecan Street Project to study integrating electric vehicle charging and driver behavioral patterns with the bulk electric system. This research project looks at the viability of EVs to intelligently charge in a distributed fashion and provide ancillary services.

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