AIR QUALITY IMPACTS OF
ELECTRIC VEHICLE ADOPTION IN TEXAS

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ABSTRACT

Widespread adoption of plug-in electric vehicles (PEVs) may substantially reduce emissions of greenhouse gases while improving regional air quality, increasing energy security, and taking advantage of inexpensive solar power. However, outcomes depend heavily on the electricity generation process, power plant locations, and vehicle use decisions. This paper provides a clear methodology for predicting PEV emissions impacts by anticipating battery-charging decisions and power plant energy sources across Texas. Life-cycle impacts of vehicle production and use and Texans' exposure to emissions are also computed and monetized. This study reveals to what extent PEVs are more environmentally friendly, for most pollutant species, than conventional passenger cars in Texas, after recognizing the emissions and energy impacts of battery provision and other manufacturing processes. Results indicate that PEVs on today's grid can reduce GHGs, NO_x, PM_{10}, and CO in urban areas, but generate significantly higher emissions of SO_2 than existing light-duty vehicles. Use of coal for electricity production is a primary concern for PEV growth, but the energy security benefits of electrified vehicle-miles endure.

As conventional vehicle emissions rates improve, it appears that the power grids must follow suit (by improving emissions technologies and/or shifting toward cleaner generation sources) to compete on an emissions-monetized basis with PEVs in many locations. Moreover, while PEV pollution impacts may shift to more remote (power-plant) locations, dense urban populations remain most strongly affected by local power plant emissions in many Texas locations.

BACKGROUND AND INTRODUCTION

Plug-in electric vehicles (PEVs) are becoming more popular in the United States and around the world. As of early 2013, the U.S. held an estimated 70,000 PEVs, nearly 40% of the world's total of over 180,000 (IEA 2013). Since PEVs were reintroduced more strongly into the passenger vehicle market in the early 21st century, researchers and policy makers have been considering the short- and long-term impacts of PEVs on energy, electricity and transportation infrastructure, and the environment. Much of the discussion includes uncertainty regarding consumer adoption and technological development of vehicles and energy infrastructure and whether or not PEVs can reduce the externalities of driving. Despite these uncertainties, many believe that PEV market shares will continue growing in the next few decades (Balducci 2008, Musti and Kockelman 2011, Becker and Sidhu 2009) and that this trend, in most cases, will reduce greenhouse gas (GHG) emissions (Anair and Mahmassani 2012, Stephan and Sullivan 2008, Samaras and Meisterling 2008) and improve air quality (Sioshansi and Denholm 2009, Thompson et al. 2009).

Even as many adopt an optimistic tone towards PEVs, others cite some concerns. Anair and Mahmassani (2012), for instance, note that PEVs can pollute more than some of the cleanest conventional vehicles (CVs) when fueled by "dirtier" electricity grids (powered mostly by coal). They suggest that in such locations (e.g., Colorado and the U.S.'s Midwest) driving an efficient (gasoline-powered) hybrid-electric vehicle will be less harmful (in terms of GHG emissions) than driving a PEV. However, they also note that places like the Pacific Northwest, which sources a large portion of electricity from non-emitting hydroelectric dams, enjoy very low per-mile GHG emissions relative to CVs.

Other concerns with PEVs include the energy demands and pollution involved in battery production and disposal and the greater energy required to produce lighter-weight materials (Hawkins et al. 2012). There is also the potential for driving rebound due to reductions in costs and perceived environmental impacts, causing some owners to increase their energy consumption (Greening et al. 2000).

Furthermore, such limitations are seen in the context of an increasingly clean CV landscape, diminishing PEVs' perceived environmental advantages. Vehicles powered by fossil fuels are producing fewer emissions and becoming more fuel efficient, thanks to increasingly strict standards. Understanding and predicting these trends is crucial to anticipating the transportation sector's energy demands, air quality impacts, and greenhouse gas emissions. While much has been written on this subject, uncertainty remains regarding how electric vehicles impact specific markets and regions.

This work offers a modeling framework to translate electrified driving (and battery charging) to equivalent per-mile emissions of GHGs and pollutants, and their spatial distribution (from tailpipes to power plants). The model is applied to the Texas region, with its mostly isolated power grid (covering most of the state) and many populated (and still growing) urban areas, where air quality is a concern.

Electricity Generation in Texas

As pointed out by Anair and Mahmassani (2012), PEVs' emissions impacts depend on the power grid used to charge the vehicle batteries. Texas's electricity grid covers nearly 90% of the state's population, and serves as an excellent study location, since regional demand can be directly linked to a single grid (as opposed to other, interconnected grids that distribute power across multiple independent system operators, or ISOs). The Electric Reliability Corporation of Texas (ERCOT) is one of the U.S.'s nine ISOs and manages the Texas grid by dispatching power and anticipating short- and long-term electricity demands. 195 of Texas's 254 counties lie within the ERCOT grid, which includes Dallas-Fort Worth, Houston, San Antonio, and Austin, constituting the nation's 4th, 5th, 25th, and 35th most populous metropolitan statistical areas (MSAs) (Census 2010). Table 1 describes the ERCOT coverage area and Figure 1 displays the spatial distribution of all electricity generating units (EGUs), by fuel type, across the ERCOT grid.

Table 1: ERCOT Grid Characteristics

Area	212,571 (mi^2)
% Texas Land Area	79.0%
2010 Census Population	22.3 million
% Total Texas Population	88.8%
EGUs	550
Transmission Line Miles	40,453

Notes: Texas' land area was measured as 268,943 mi^2 using ArcGIS, and its 2010 population was 25,145,561 persons. Sources: U.S. Census (2010), EPA (2012), & ERCOT (2012).

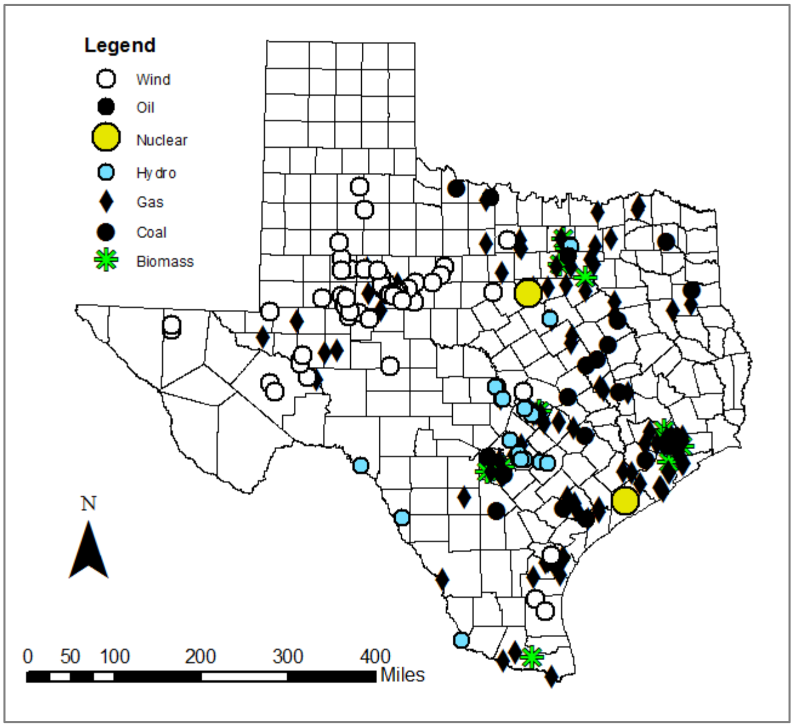

Figure 1: ERCOT Power Plant Locations by Fuel Type

ERCOT (2012) expects (instantaneous) peak demand for its electricity to increase around 45% over the next 20 years (by 2033), growing to over 96,000 MW from the current peak of nearly 67,000 MW. However, ERCOT (2012) anticipates fuel type shares to remain relatively constant across the next ten years, with the predicted coal shares decreasing nearly 2% (from 25.5% of total generation in 2013 to 23.7% in 2022) and gas share increasing nearly 1% (from 64.1%. in 2013 to 65.0% in 2022). This forecast is more static than nationwide forecasts, which anticipate a 6% drop in coal shares (from 45% of total generation in 2010 to 39% in 2020) and a 1.5% increase in natural gas shares (from 24% in 2010 to around 26.5% in 2020) (EIA 2012). Given these rather minor shifts in power feed stocks, the fuel share mix is assumed constant in this analysis's future projections. However, even with a consistent mix, emissions rates may change as older, less efficient plants are decommissioned and newer facilities (of the same fuel type) replace them. An analysis of emissions rates as a function of construction date (first year the EGU was online) from eGRID shows weak trends, suggesting that many older ERCOT plants may have been retrofitted, and/or that not all new plants are built to a low-emissions standard.

The ERCOT grid now functions as a nodal market, rather than a more traditional zonal market, meaning that power can be distributed more evenly across the entire grid, rather than shifted across geographic zones. This distinction mostly refers to how electricity pricing is managed, and was implemented to reduce transmission line congestion and prompt new EGU construction along less congested lines (Dyer 2011). This market structure impacts PEV emissions analysis, since electricity consumed at any point on the ERCOT grid can come from any generation facility on the grid. In other words, this structure removes any geographical constraints between electricity producers and consumers, and emphasizes providers that can produce electricity at the lowest marginal cost, reflecting both production costs and transmission losses. This makes it very difficult to relate PEV charging demand to point-source emissions locations, without incorporating an economic dispatch model.

Emissions and Air Quality

One criticism of PEVs driving electrified miles is that they are not "zero emissions" vehicles: they produce significant emissions during manufacture, and shift operating emissions from the tailpipe to other locations. Some have argued that PEVs can be worse for the environment, by producing more life-cycle GHG emissions, though the impacts may be obscured by geographical distance and the fact that many impacts occur during upstream production phases (Hawkins et al. 2012, National Research Council 2010, Alonso et al. 2012). Regardless of how overall PEV energy demands compare to those of CVs, it is true that PEVs shift many of their operating emissions (for all miles that are "electrified") from the point of usage (a roadway) to a sometimes very distant point source. PEV users driving off battery power and others in their usage area benefit from zero tailpipe emissions, but populations surrounding the power generator for any electrified miles will generally be subject to more air pollution. The accounting framework is complicated by the inclusion of plug-in *hybrid* electric vehicles (PHEVs), since their drive-cycles (and thus emissions) can (and regularly do) fluctuate between battery and gasoline sources of motive power. The emissions shifting situation, over space, also presents ethical dilemmas and may encourage more driving, by reducing users' perceptions of their environmental impacts (Hertwich 2008). However, reducing exposure of highly populated urban areas (where many more human lungs are present) may be a real benefit of such emissions exporting.

One approach to addressing this problem is to view emissions objectively, by considering population exposures from power plants producing PEVs' electricity. This is rather challenging to model with certainty, since individual plant generation fluctuates, but it is possible to consider average emissions rates, based on past usage, and to analyze affected populations within a certain range. Defining a range of exposure is also difficult, though, since health and other impacts vary by pollutant type, weather, micro-climates, and individuals' health, behavior, and outdoor exposure. This study leaves such details to air quality modelers and epidemiologists, and evaluates aggregate emissions exposure rates, taken as the product of annual EGU emissions and surrounding population.

Some of the most harmful byproducts from both vehicles and power plants are particulate matter, carbon monoxide, and nitrogen oxides. In the U.S., all vehicles (cars, trucks, buses and off-road vehicles) produce over half of the nation's anthropogenically-derived smog-forming volatile organic compounds (VOCs) and nitrogen oxides (NO_x), and around three-quarters of total carbon monoxide (CO) emissions (EPA 2012). These pollutants damage health directly, and/or react to produce ozone, acid rain, fine particulate matter, and other secondary pollutants.

Many U.S. regions are interested in improving air quality to avoid violating the EPA's National Ambient Air Quality Standards (NAAQS). With many Texas regions currently in non-attainment or near-non-attainment for ozone, while experiencing continuing population and VMT growth, PEVs present an opportunity for improved air quality and lower energy demands. However, it is unclear just how much of a benefit PEVs might have for specific locations, and whether shifting from on-road to point-source (power plant) emissions will result in significant net benefits.

METHODS

This research translates anticipated PEV demands to emissions over time and space, from tailpipes and power plants across Texas's electricity grid. The emissions impacts are evaluated relative to conventional (gasoline-powered) passenger vehicles (CVs). Several different model components are considered here, including vehicle ownership and use, charging behaviors, power production, and emissions from both vehicle manufacture and vehicle operations. The following sections consider how readily PEVs may be adopted, how they will be used and charged, and their power demands over time

Anticipating PEV Ownership

Although PEVs are the subject of extensive research, very little PEV ownership and usage data is made publicly available. State vehicle registries do try to count EVs and include vehicle location and owner information, but this data is rarely released for research (or is provided at a cost). Some private databases do exist, but PEVs are such a new vehicle class that no large surveys (such as the National Household Travel Survey [NHTS]) include sufficient sample sizes. The most recent version of the NHTS dates to 2009, and includes only 15 total PEVs, out of 309,163 total vehicles (NHTS 2009). In many cases ownership data is unavailable, due to such small sample sizes and confidentiality concerns for owners, as well as vehicle identification numbers (or VINs) that can change yearly for specific makes, models and styles of vehicles, hindering states' EV accounting and any related research.

As a result, a rather straightforward approach for anticipating PEV emissions impacts is pursued here, by defining a set of reasonable yet hypothetical adoption scenarios. Since emissions are measured across the entire ERCOT power grid (i.e., any power plant may provide the power to charge a PEV), the actual ownership distribution of PEVs is irrelevant for understanding average PEV emissions rates. However, PEV use locations are relevant for tailpipe emissions removal, and much of this impact may be felt in highly populated regions, where most PEV miles presumably will be driven. Future work may do well to emphasize their spatial distributions.While it may have been necessary to model PEVs' charging locations in the past, the ERCOT grid now functions as a nodal market, rather than a more traditional zonal market. As noted earlier, this means that power can be distributed evenly across the entire grid, such that an EV in south Texas may be drawing power from an EGU hundreds of miles away at Texas's northern border. This system is complicated to model at a fine scale (where each EGU's emissions are pinpointed by the exact hour of the year, for instance), but it does simplify the process of electricity demand from PEVs into a more aggregate approach. PEV shares of 1%, 5%, 10%, and 25% of all light-duty passenger vehicles are evaluated here.

From these shares, the total number of EVs can be estimated from vehicle-registration data at the county level. The Texas Department of Motor Vehicles provides counts of registered light-duty vehicles (LDVs) and total vehicles (including fleet vehicles and trucks) for as recent as 2009, and total vehicle registrations up to year 2012. LDV counts are not available for 2012, but were estimated here using the year-2009 shares, in each county. Only counties within the ERCOT region were selected for this analysis, to represent vehicles that are typically charging at locations on the ERCOT grid. Table 2 reports registration totals for all Texas counties and the ERCOT study region, by vehicle type and year. It is assumed that the share of LDVs (relative to all registered vehicles in Texas) remains constant from 2009 to 2012. Population data were provided by Texas Department of State Health Services (TDSHS 2009).

Table 2: Vehicle Registration across ERCOT Counties

	All Texas Counties		ERCOT Study Region	
	2009	**2012**	**2009**	**2012**
Total Vehicle Registrations	21,432,323	22,768,989	18,883,629	20,117,012
Light-Duty Vehicles	16,476,921	17,512,296	14,623,814	15,581,975
Average % LDV	64.9%	64.9%	64.9%	64.9%
Population	24,782,302	26,403,743	21,845,465	23,360,309
LDVs per Capita	0.66	0.62	0.67	0.63

EV Usage and Driving Behavior

Given a PEV count estimate for Texas, the next step is to estimate energy consumption of those vehicles, based on driving and charging behaviors, and therefore electricity demand via PEV charging. EVs may be used differently from conventional vehicles, thanks mostly to BEV range limitations (see, e.g., Khan and Kockelman 2012, Kang and Recker 2009). Also, the efficiency and often drive cycles of EVs can be quite distinctive. Karabasoglu and Michalek (2012) noted how electrified driving cycles can affect energy consumption in a manner rather opposite that of CVs. Specifically, they suggest that PEVs consume less energy in high congestion, city driving, versus CVs, but actually consume slightly more energy than CVs during constant highway driving.

Though these distinctions are meaningful to consider, especially when evaluating the benefits of PEVs on a transportation network, this study applies at a rather aggregate level, and so relies on average estimates for PEV owner behaviors. Specifically, the EV use assumptions used here come from extensive GPS-based data of Chevrolet Volt and Nissan Leaf use across the United States, from the EV Project (ECOtality 2013). The EV Project is a joint study between research groups at the U.S. Department of Energy and Idaho National Laboratory, and industry supporters at Nissan, Chevrolet, and Ecotality (an EV Supply Equipment provider), and other various agency and industry partners. The EV Project releases quarterly summary data for vehicle electricity demand and miles traveled, for several locations across the U.S., including two Texas cities: Dallas and Houston. However, sample sizes are rather small for these two cities, especially for the BEV Nissan Leaf. Therefore, U.S. averages for driving distances between charges, and electricity use rates (Wh/mile) are used here, over all quarters of the years in which EV Project data were collected: these range from Quarter 1 (Q1) in 2012 through Quarter 2 (Q2) in 2013.[1] Table 3 reports these averages for values in the emissions model.

Table 3: Average Use of EV Project Fleet

	BEV (Nissan Leaf)	PHEV (Chevrolet Volt)
Avg. Daily Distance Traveled[2]	29.73 mi	39.7 mi

[1] Quarters are defined as follows: Q1 January to March, Q2 April to June, Q3 July to September, Q4 October to December.
[2] Average distance considers only distance traveled only on days traveled.

Avg. Distance between Charge Events	27.05 mi	27.2 mi
Efficiency	300 Wh/mi	245 (Wh/mi)
Gasoline Fuel Economy	n/a	35.5 mi/gal
% Total Distance in ERM	0%	26.5%

Electric Vehicle Emissions Model

This section discusses the process of translating PEV behaviors and assumptions from the usage model discussed above into emissions estimates from Texas's power grid. This approach reflects demand and emissions variations at the 15-minute interval, but is only useful for understanding emissions inventories at an aggregate level, since one cannot predict the spatial distribution of (point source) emissions from ERCOT's power plants. Some discussion on life-cycle emissions is also presented, later in this section, to provide a more holistic approach to PEV emissions estimation.

Combining usage estimates with total vehicle assumptions produces total daily electricity demand (by multiplying average daily distance traveled by motor efficiency). This calculation requires estimates BEV and PHEV shares, to determine electrified miles versus extended-range-mode (ERM) miles. This study examines variable shares, from 0% BEVs and 100% PHEVs, to 100% BEVs and 0% PHEVs, at 25% increments. Average daily electricity demand from BEVs in year *i* under adoption scenario *j* (D_{ij}) is calculated as follows:

$$D_{ij} = ((\eta \times \alpha_{BEV} \times d_{BEV}) + (\eta \times (1 - \alpha_{BEV}) \times d_{PHEV} \times (1 - \beta)) \times m_{ij}$$

where η is battery efficiency (in miles/Wh), α_{BEV} is the share of EVs that are BEVs, d_{BEV} and d_{PHEV} are average daily miles traveled by each BEV and PHEV, respectively, β is the average share of daily distance that PHEVs drive in extended-range mode (which is analog to the "utility factor", estimated to be around 70 percent by Khan and Kockelman [2012]), and *m* is the total number of EVs in the study area, in year *i* and under adoption scenario *j*. Note that all these values are constant across *i* and *j*, except for the number of EVs or m_{ij}.

Average daily electricity demand (D_{ij}) provides a baseline for estimating aggregate load on the ERCOT electricity system, but determining generating emissions requires more nuance. For instance, the time-of-day at which a PEV draws power influences the overall emissions profile for that marginal electricity consumption, since demand profiles for electricity change over time as residents, businesses, and industry use electricity for different purposes, and in response to diurnal weather conditions. Similarly, electricity demand is affected by season, as heating and cooling demands vary. Therefore, the time of-day at which EVs are charging is important for anticipating upstream generator emissions.

The EV Project (2013) publishes quarter-hour charging profiles, which were matched to grid generation shares. Quarterly averages of total AC demand in kWh from the EV Project were normalized by the maximum demand during the quarter, to produce standard demand profiles that can applied to any level of electricity demand. For example, if the maximum electricity demanded from BEVs during a 15-minute interval is 0.0475 kWh at 7 PM, all other 15-minute interval demands were divided by this amount to create a maximum value of 1.0 at 7 PM.

The EV Project data considers weekday and weekend charging behaviors, so those two empirical charging profiles were considered. Additionally, two theoretical charging behaviors were explored – a concentrated peak demand, and an off-peak demand. The concentrated peak demand is considered a "convenience" charge, in an approach borrowed from Thompson et al. (2011) that represents all EVs starting to charge right after returning home from work (or other activities), at 5pm, when electricity demand is generally peaking (due to households and business being "on" at the same time, and Texas homes cooling down during an especially hot time of day during the summer months). This approach condenses all EV electricity demand into a span of 7 hours, from 5 pm to 12 am. Conversely, an off-peak (nighttime) profile was chosen in a way to reduce emissions, by taking advantage of higher renewable (wind) shares, and fewer peak plant emissions in the late night and early morning hours. These profiles are normalized as well, so that total electricity demand is constant across each 15-minute interval, during the charging period. Figure 2 shows the four different (normalized) charging profiles.

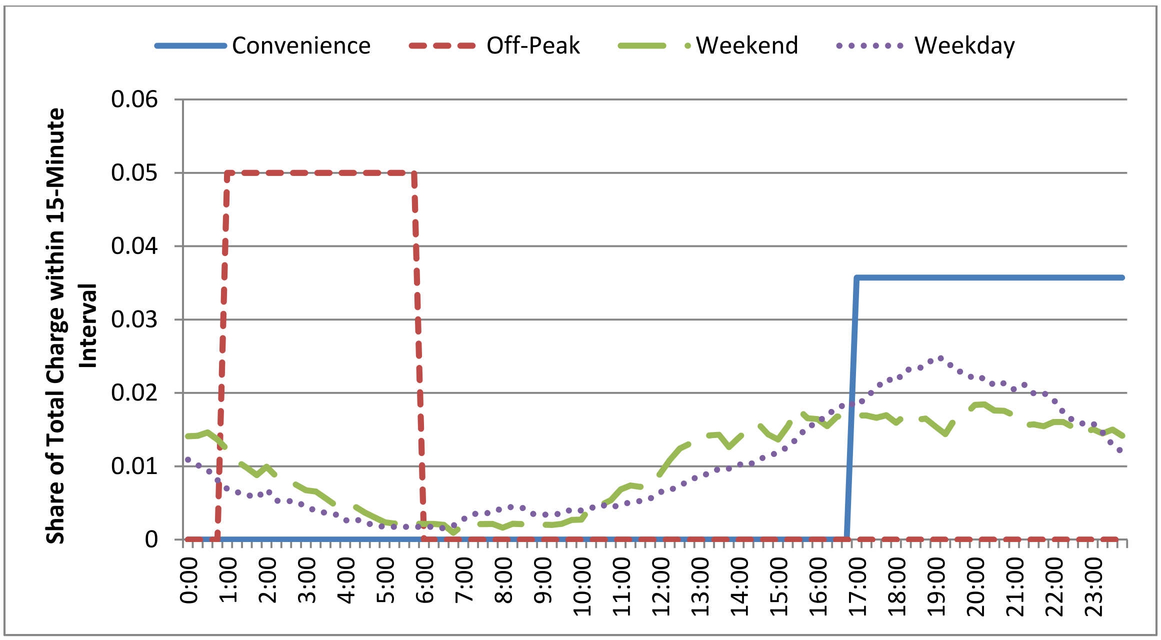

Figure 2: Normalized Charging Profile

The energy E consumed from an EV fleet charging on ERCOT's grid for a 15-minute time interval t is calculated as follows:

$$E_t = D_{ij} \times \frac{d_t}{\sum_t d_t}$$

where d_t is the average electricity demand in time-interval t, using EV Project estimates. With this specification, total EV energy demands are spread out across 15-minute intervals concurrent with actual average profiles. EV Project data provide multiple quarterly demand profiles, including maximum and minimum values, as well as inner and outer quartiles. This study simply relies on the median demand value for a weekday. These demand profiles are specific for each quarter, based on the only year for which a complete set of EV Project charging data was available at the time of this research: 2012.

After determining time-specific total electricity demand across different BEV adoption scenarios, electrified-mile emissions can be estimated. Emissions estimation now becomes more complex, with unique electricity generating units (EGUs) entering as model components. Quarter-hour emissions rate tables were matched with interval electricity demands to determine daily and annual BEV emissions. Emissions rate tables for 6 pollutants (NO_x, SO_2, CH_4, N_2O, CO_eeq, PM_{10}, CO, and VOC) were developed at 15-minute intervals for all 4 quarters of 2012 on the ERCOT grid using emissions data from the eGRID database (EPA 2012) and National Emissions Inventory (EPA 2001).[3] These data provide emissions rates for each of the 550 power generators on the ERCOT grid. Weighted average emissions rates for pollutant *p* are calculated for each fuel type *f* (coal, natural gas, oil, and biomass) based on annual emissions (*A*) per power plant *z*, as follows:

$$w_{pf} = \frac{x_{fpz} \times A_{fz}}{\sum_z A_z}$$

where x_{fpz} is the emissions rate for pollutant *p* of plant *z* combusting fuel type *f*. These emissions rates represent the marginal emissions of consuming one MWh of electricity by using a specific fuel type *f*. Total marginal grid emissions of each pollutant (*e*), therefore, are a function of fuel type shares (y_f) , weighted-average emissions rates, and interval energy demand (E_t) for PEV charging. While weighted emissions rates were assumed constant, fuel type shares change over time and by season. These changes are incorporated based on 15-minute ERCOT generation data, by fuel source, for every day in 2012. Simple averages of total production (per time interval [*t*]) were calculated for each quarter (*k*) to produce quarterly average fuel type shares (y_{fkt}). Therefore, quarterly emissions rates can be calculated as follows:

$$e_{pkt} = \sum_f y_{fkt} w_{pf} E_t$$

This approach takes into account the fact that generation fuel type shares change as demand changes over time and season, for any marginal electricity usage. By “marginal” usage, it is assumed that the total PEV demand (D_{ij}) does not affect the generation fuel type shares. In some cases, where PEV demand is very high, additional EGUs may be required to meet demand. At present, Texas’s small PEV population has only a marginal effect on the grid, but if demand increases, perhaps even to 5% of total LDVs, this marginal demand assumption may no longer hold.

The final result for this approach is a lookup table of quarter-hour emissions rates, by season for 8 different pollutants. This is the table multiplied by total daily demand to determine daily emissions impacts of PEV charging. The result is in terms of aggregate emissions, but results could also be evaluated geographically by considering individual generator locations and proximity to urban areas.

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[3] Emissions for NO_x, SO_2, CH_4, N_2O and CO_2eq were taken from actual plant emissions, as found in the eGRID data set, while PM_{10}, CO, and VOC are based only on grid-wide averages by fuel type, from the National Emissions Inventory Data set. These average rates were computed by dividing annual emissions from all plants of a given fuel type by the annual electricity generation. Therefore, these are unweighted estimates, compared to eGRID estimates, which are weighted by generation of each plant across a given fuel type.

It should be noted that the ERCOT generation mix data separates natural gas plants into two types: traditional and combined cycle. However, eGRID emissions rates do not differentiate between these two types. ERCOT data indicate that roughly 50% of Texas's natural-gas generators (unweighted by their individual power production levels) are combined cycle. Additionally, this study considers hydroelectric, solar, wind, and nuclear generators to be non-emitting, for all pollutants considered. This assumption is based on eGRID emissions rates, but it is important to recognize that the *life-cycle* emissions of these power sources are not zero (due to emissions in the design, manufacture and maintenance of such facilities). Nuclear power is an especially controversial generating source, even though it produces zero emissions from direct generation. Risks of catastrophic meltdown and radiation exposures are a constant public concern, along with space and security demands of storing spent nuclear waste, which remains toxic for many years. Solar panels, too, require rare earth mining, while wind turbines and hydroelectric power generators can have negative impacts on wildlife habitats (Tsoutsos et al. 2005, Rosenberg et al. 1997).

Life-Cycle Considerations

For a more complete evaluation of PEV versus CV emissions implications, some attention should be paid to each vehicle's life-cycle emissions, since PEVs generally require more energy (and thereby emissions) to construct, thanks mostly to battery assembly (Hawkins et al. 2012) and use of special materials to lower weights. This analysis uses embodied energy demands directly from Argonne National Laboratory's Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model, which accounts for the upstream emissions and energy inputs required to produce all materials for typical, light-duty vehicles. These components include the various materials used, such as steel, plastic, iron, and rubber; various fluids used (e.g., engine oil, power steering fluid, brake fluid); and batteries (used in CVs and more extensively in PEVs). GREET requires many assumptions regarding vehicle weight, materials, and inputs for upstream energy and emissions from power plants and transportation sources. The analysis here simply assumes all default estimates from GREET 2.1, as originally described by Wang (2001) and revised by Argonne National Laboratory (2013). This estimate of embodied energy across CVs and PEVs provides an additional dimension for a more holistic comparison between the two vehicle types for different electricity fuel mix scenarios.

RESULTS

Average emission rates on the ERCOT grid were computed for 6 pollutant types, with results shown in Table 4. Table 4's emission rates are based on eGRID and ERCOT data that vary by time-of-day and season. Other emissions rates, provided below (for PM, CO, and VOC), are Texas-wide averages, derived from the U.S.'s National Emissions Inventory (NEI) (EPA 2001) for year 2008. NEI data is not available for direct comparison for biomass and "other" electricity combustion sources as defined in eGRID data.

Table 4: Average ERCOT Emissions Rates (lb/MWh) from eGRID 2012 (2009 rates) and NEI (2008 rates).

	NO_x	SO_2	CH_4	N_2O	CO_2eq	$PM_{2.5}$	CO	VOC
Coal	4.04	19.2	284.7	422.3	6,537.5	0.11	2.97	0.03
Natural Gas	0.28	0.006	52.6	5.4	671.8	0.04	0.12	0.02

Other	0.11	1.8	28.1	41.2	641.6	--	--	--
Biomass	2.06E-4	1.41E-5	0.276	0.037	0.004	--	--	--
Renewables, Nuclear	0	0	0	0	0	0		0

Note: SO_2 is a significant precursor of harmful PM2.5 downwind of the EGU.

These rates were then used to determine the emissions of electricity demand from PEV use, given a variable mix of these fuel types on the grid's feedstock. Figure 3 shows the anticipated shares, at 15-minute intervals, for Q1 (winter-spring).

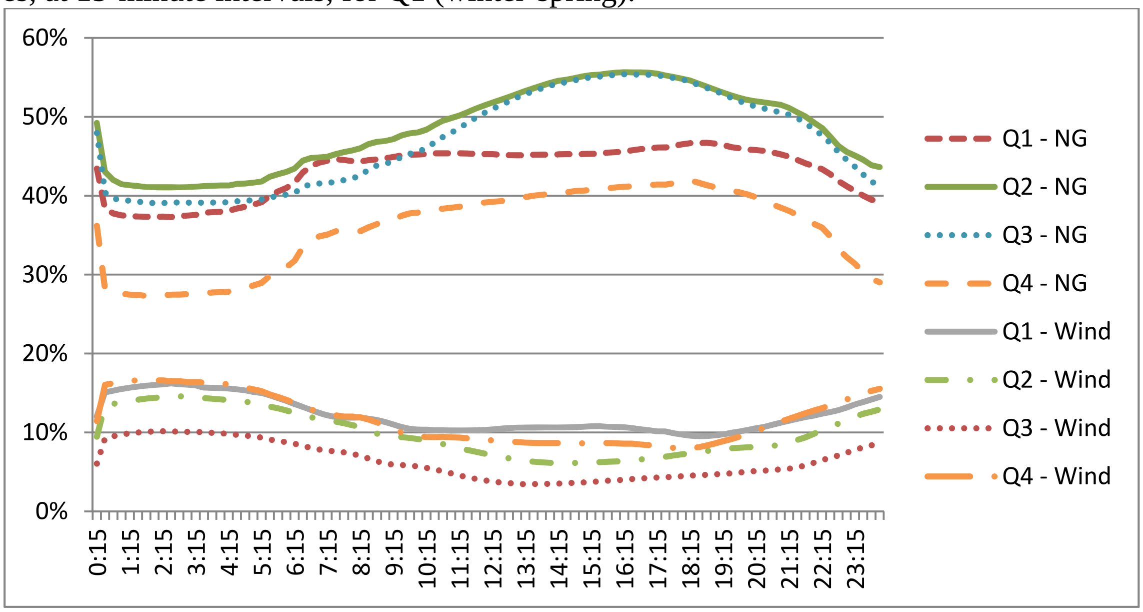

Figure 3: Average ERCOT Electricity Shares by Energy Source, Time of Day, and Season

Comparing different charging profiles indicates little difference between charging scenarios, as shown in Table 5. This result is consistent with Thompson et al.'s (2011) findings of almost no difference between 4 different EV-charging profiles on the Texas grid.

Table 5: Average Electrified-Mile Emissions Rates by Charging Scenario on ERCOT grid (grams/mi)

Charging Scenario	**NO_x**	**SO_2**	**CH_4**	**N_2O**	**CO_2eq**
Weekday	0.166	0.721	13.34	16.13	279.41
Weekend	0.165	0.722	13.33	16.16	279.48
Convenience	0.167	0.724	13.39	16.21	280.56
Off-Peak	0.166	0.732	13.02	16.33	276.95

Table 5's differences are rather small, and nearly negligible, with the exception of perhaps CO_2eq. The rate difference from all PEVs charging when convenient (i.e., right when they arrive home) versus off-peak (for power generation) is about 6,730 tons of CO_2eq per year, or just a 1.3% decrease in grams per electrified mile of CO_2eq emissions. Zivin et al. (2012) also studied temporal variations in CO_2 emissions and noted that the ERCOT grid is one of the most stable over times of day, as compared to the eastern and western (WECC) interconnections. Since little difference appears to exist by time of day in Texas, assuming average grid mixes (rather than a special, generator-specific dispatch model), the state's weekday charging emissions profile was assumed, to provide the following results.

Note that in Table 5 and the following discussions, only NO_x, SO_2, CH_4, N_2O and CO_2eq are considered. The detailed eGRID data does not include other important pollutants such as CO, PM and VOCs, though they are considered in average terms in later analysis, based on results from Table 4.

Conventional Vehicle Emissions

Average PEV emissions were compared to those of four different CV types, as shown in Table 6, in order to evaluate PEVs' relative emissions profiles. For this evaluation, emissions rates for gasoline- and diesel-powered passenger cars and light-duty trucks (like SUVs, minivans, and pickups) were estimated using EPA's MOVES model, as shown in Table 6 (and developed for use in Kockelman et al.'s [2012] Project Evaluation Toolkit, for Texas applications). Table 6's CV rates correspond to an average of rates estimated for Dallas, Waco, and Houston conditions in the summer of 2010, for vehicles traveling at 30 miles per hour, which is close to the average commute speed of 27 mph reported by the National Household Travel Survey (NHTS 2009).

Table 6: CV vs. PEV Operating Emissions Rates (grams/mile)

	NO_x	SO_2	PM_{10}	CO	VOC	CH_4	N_2O	CO_2eq
Gas Passenger Car	0.3739	0.00769	0.0310	3.3905	0.1518	0.00579	0.00316	393.92
Diesel Passenger Car	1.0104	0.00341	0.0689	0.5373	0.0682	0.00166	0.00057	436.76
Gas Light Passenger Truck	0.8869	0.01055	0.0443	7.0989	0.3387	0.01121	0.00889	540.69
Diesel Light Passenger Truck	3.8152	0.00574	0.2746	4.1980	0.6237	0.01010	0.00221	728.29
BEV 2012 Avg. ERCOT Mix	0.17	0.72	**0.014**	**0.15**	**0.002**	13.34	16.13	**280**
BEV 2012: 100% Coal	0.47	2.23	0.036	**0.43**	**0.005**	33.14	49.15	761
BEV 2012: 100% NG	**0.03**	**0.00**	**0.005**	**0.02**	**0.002**	6.12	0.63	**78**
BEV: 25% Increase in	**0.12**	0.54	**0.011**	**0.11**	**0.002**	10	12.1	**210**

Note: Bold indicates BEV emissions rates that are lower than all CV averages.

Note that these results do not include CVs' cold start emissions, which are higher (per mile traveled) than standard operating emissions, since emissions-control equipment (like the catalytic converters) have not reached optimal activation temperatures (Frey et al. 2002). However, preliminary analysis suggested that broadly considering cold starts did not appreciably change the overall research findings. Finer-scale models that consider detailed trip behavior should consider cold starts for a more comprehensive analysis.

Both CVs and PEVs are projected to experience significant improvements in emissions in coming years. The Environmental Protection Agency's Tier 3 Vehicle Emission and Fuel Standards Program will harmonize national regulations with existing California Air Resources

Board (CARB) Low Emission Vehicle (LEV III) standards, resulting in an estimated 56% reduction in SO_2 by 2018 (EPA 2014b). SO_2 emissions from coal-fired power plants, already at record lows, are projected to drop by another two-thirds from 2011 to 2016 (EIA 2013). Electricity generation with fuels other than coal will result in even lower pollutant emissions.

These results highlight some major emissions profile differences between electrified miles (by BEVs or PEVs in electric mode) and CV driving. The most striking difference is the considerably higher SO_2 emissions from BEVs using the average ERCOT feedstock mix, which is over 70 times higher than that of the average CV. Emissions of two particular greenhouse gases - methane (CH_4) and nitrous oxide (N_2O) - are also much higher for BEV miles in all feedstock mix scenarios, yet overall CO_2 emissions are lower in most cases for BEVs (except when powered solely by coal). A key concern here is that electrified miles relying exclusively on power from Texas's average coal-fired power plants produce more than *twice* the CO_2 of a typical gasoline-powered passenger car, 125% more GHGs than a diesel passenger car, and many more times methane and nitrous oxide than CVs, per mile traveled. The GHG difference between a gasoline-powered SUV (or LDT) and coal-powered BEV passenger car is less pronounced, suggesting about a 20% increase for the BEV car, but still underscores the inherent inefficiency of using a BEV with a dirty fuel source. Fortunately, Texas' average electric-power presently produces about 25% less CO_2 per mile traveled on pure battery power than a typical gasoline-powered car.

BEVs are expected to produce less NO_x, PM_{10}, VOC, and CO emissions than the average CV under most Texas-power scenarios - except for the case of 100% coal combustion. This shift in emissions offers valuable solutions to various urban air quality concerns. For example, many U.S. regions are in non-attainment or near non-attainment with the national ozone standard (EPA 2013), and so will benefit from lower overall NO_x and VOC levels (Farooqui, et al 2013).

The margin between today's grid emissions and existing CV emissions is only large for CO and VOC, and quite thin for NO_x and PM_{10}. For instance, an average BEV's PM_{10} emissions on the existing grid nearly equal those of the average gasoline car, and BEV's NO_x emissions are about half those of such a car. Though this latter difference is significant, both CV and power plant emissions rates are likely to change. The conventional vehicle fleet is expected to become cleaner, thanks to older, more polluting vehicles being removed from roadways, and better emissions control systems on newer models. The EPA has long been pushing for reduced power plant emissions, especially from coal plants, but the extent of those gains is currently unclear. Changes in the auto industry are expected thanks to the recently-passed Tier 3 emissions standards (EPA 2014b) and CAFE (fuel economy) standards up through 2025. These emissions improvements are expected to be rather significant, as shown below for passenger cars, based on PET's MOVES-based emissions estimates through 2025.

Table 7: CV Emissions Changes to 2025 (grams/mile)

	NO_x	SO_2	PM_{10}	CO	VOC	CH_4	N_2O	CO_2eq
2010 Gas Passenger Car	0.3739	0.008	0.0310	3.3905	0.1518	0.00579	0.00316	393.92
2015 Gas Passenger Car	0.1760	0.007	0.0303	2.4759	0.0723	0.00386	0.00174	381.17

2020 Gas Passenger Car	0.0928	0.007	0.0300	2.0677	0.0466	0.00346	0.00144	347.40
2025 Gas Passenger Car	0.0678	0.006	0.0300	1.9627	0.0407	0.00332	0.00136	324.18
BEV 2012 Avg. ERCOT Mix	0.17	0.72	**0.014**	**0.15**	**0.002**	13.34	16.13	**280**
BEV 2012: 100% Coal	0.47	2.23	0.036	**0.43**	**0.005**	33.14	49.15	761
BEV 2012: 100% NG	**0.03**	**0.00**	**0.005**	**0.02**	**0.002**	6.12	0.63	**78**
BEV: 25% Increase in	**0.12**	0.54	**0.011**	**0.11**	**0.002**	10	12.1	**210**

If CVs do achieve such emissions reductions, BEVs using today's average ERCOT electricity may no longer provide such clear air quality benefits. For instance, average ERCOT-based NO_x emissions for electrified miles are currently about half those of a 2010 passenger car, but may become *twice* those of such CVs if LDV emissions rates improve and grid emissions stay constant. Though power-grid emissions improvements are expected (EPA 2014a, the turnover rate of older and less efficient power plants is likely lower than that of vehicles. Of course, domestic power provision also offers greater energy security, and EVs can be powered using a variety of "emissions-free" renewable feedstocks, including distributed (household-level) solar panels.

Life-Cycle Analysis Comparison

Though the previous analysis provides some insight into the relative emissions profiles of vehicle use, consideration should be given to differences in emissions from vehicle production phases. This is done by including GREET's embodied emissions results alongside operating emissions, as shown in Figure 4. Another source of such estimates is Michalek et al. (2011), who have estimated high embodied energy implications for EVs.

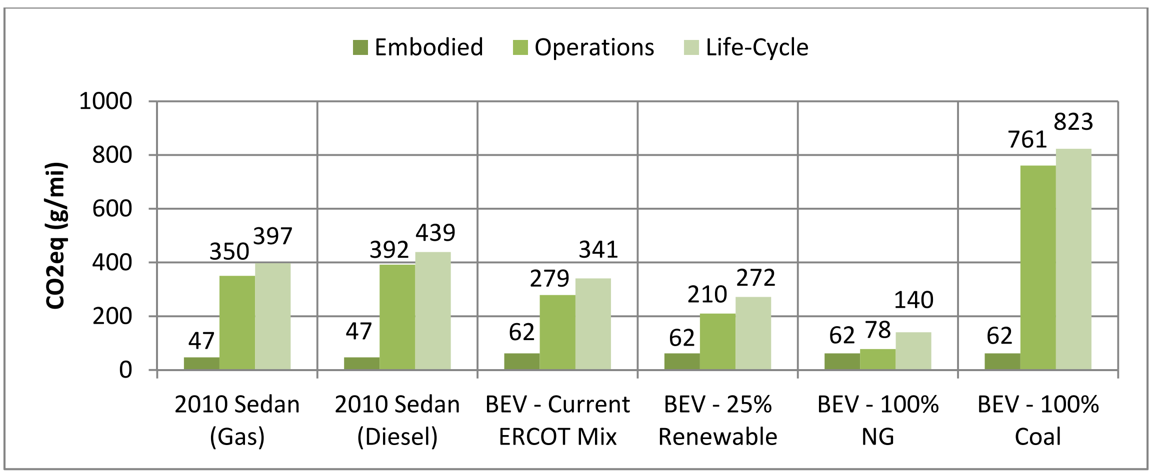

Figure 4: Life-Cycle CO_2eq Emissions of CVs vs. BEV Scenarios

This analysis suggests that most life-cycle energy for conventional vehicles, and BEVs fueled by coal, is from daily driving rather than from production phases. Although BEV production might produce around 30% more CO_2eq than conventional vehicles, this phase is rather insignificant when compared to operations emissions. In fact, embodied energy comprised only about 11 and 7% of GHG emissions of gasoline and diesel vehicles respectively. A critical point to consider here is the life-cycle GHG emissions of conventional vehicles and BEVs using the current mix. These results suggest that BEVs produce around 18% less GHG per mile than CVs, and that this reduction could reach 35% with an increased share of renewables or nearly two-thirds with a 100% natural gas source.

A similar analysis can be performed for NO_x, which is critical for meeting U.S. air quality standards (as discussed above). Results are shown in Figure 5.

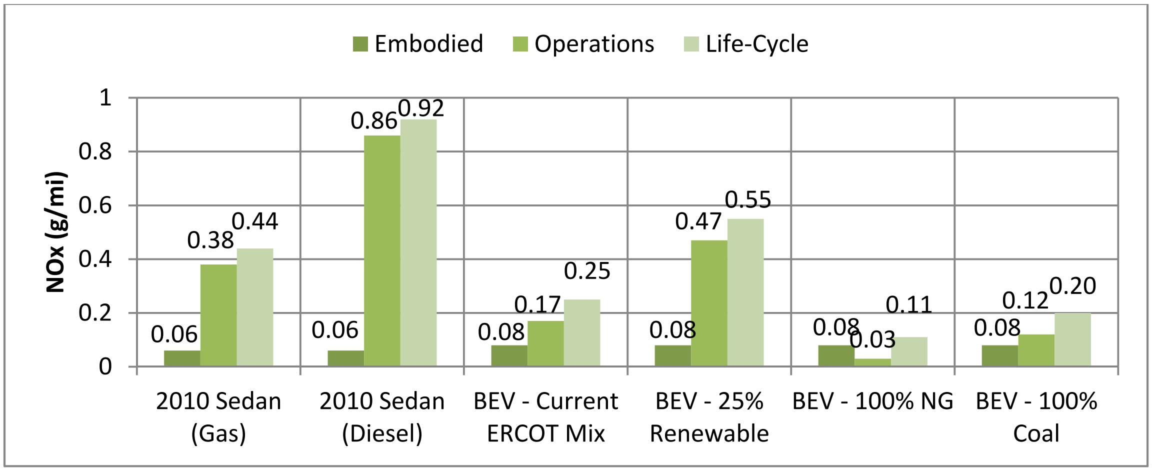

Figure 5: Life-Cycle NOx Emissions of CVs vs. BEV Scenarios

It is interesting to note that, for the 100% NG scenarios, the operations phase produces fewer NO_x emissions than the embodied phase, which reverses the traditional ordering found for other vehicle types and fuel mix scenarios. CO_2eq emissions mimic this trend as well, with operations and embodied energy sources nearly equal for a 100% NG scenario, at least when assuming the relatively efficient generator types used on the ERCOT grid.

There is one emissions-species case studied here where BEVs, under any fuel mix scenario other than 100% renewables, perform worse than CVs; this is the case of SO_2 emissions. Figure 6 shows that the average gasoline and diesel sedan produces very little on-road SO_2, as compared to SO_2 from electricity generation. SO_2 causes both respiratory ailments (Chen et al. 2012, Frank et al. 1962) and contributes to acid rain (Park 1987).

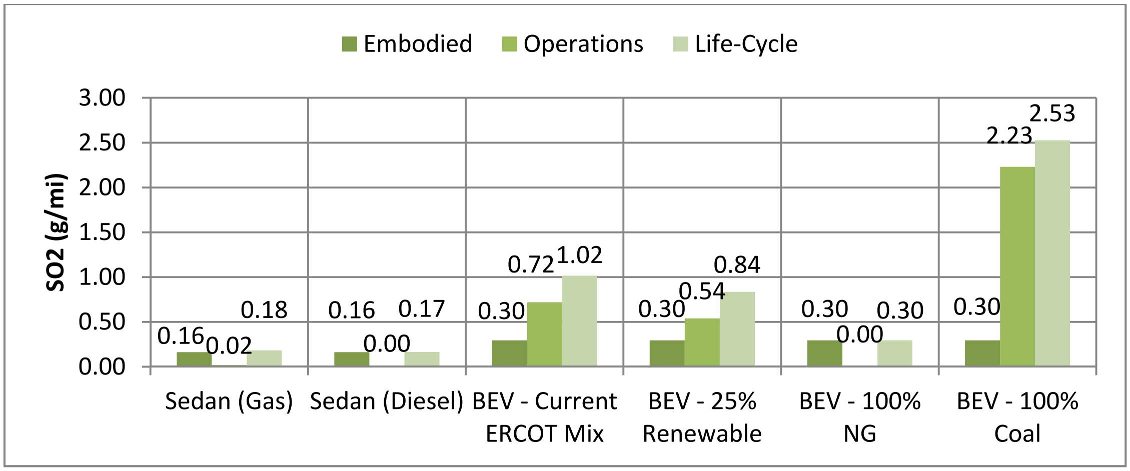

Figure 6: Life-Cycle SO_2 Emissions of CVs vs. BEV Scenarios

It should be noted that this life-cycle analysis does not necessarily consider the embodied energy associated with fuel production or power generation in the operations phase. That is, for gasoline, diesel, coal, natural gas, nuclear power, and other fuels, the only input is the amount of fuel consumed in the operations phase. Since the embodied phase of energy or fuel production is neglected, the magnitude of the operations phase is thereby underestimated for all vehicles. This may influence the magnitude of operations emissions differently across CVs and BEVs, but is unlikely to make a noticeable difference, since embodied-energy implications typically average 10 percent of the total energy use and will be overshadowed by the relative differences in operations. Exploring the embodied phase of operational energy leads to a recursive and increasingly complicated analysis focused on relatively negligible marginal emissions, so they are ignored in this case.

PEV Emissions Exposure

Though previous results suggest that PEV emissions rates for air quality pollutants are in most cases lower than those for CVs (with the exception of SO_2), it is important to consider how emissions may shift over space and exposed populations, when shifting from CV use to PEV use. Thompson et al. (2009, 2011) performed rather detailed spatial emissions analysis of PEV emissions at point source locations, and that level of sophistication and expertise in air quality modeling is not replicated here. Rather, a general "exposure rate" is calculated for each ERCOT county, as the product of annual power plant emissions (in tons per year) and evenly-distributed county population. A 25-mile buffer is considered for each power plant to calculate exposure rates, and overlapping emissions exposures are summed to produce a sense of annual exposure. Though emissions can affect populations hundreds of miles away, the small buffer size used here provides more insight to geographic emissions concentrations. This measure provides a sense of where the largest overall impacts from PEV usage are likely occurring, over the long term (since at any given time any number of the modeled plants may be operating). This measure is therefore a sense of the aggregate air quality risks posed by rising PEV use.

Figure 7's results illustrate how Texas' urbanized areas experience some of the greatest total exposures to power plant emissions, which is unsurprising, given these regions' high population concentrations. However, there are some less densely-populated counties well away from

Texas's major metropolitan areas (Dallas-Fort Worth, Houston, San Antonio, and Austin) that show very high exposure rates for all power plant pollutants as shown in Figure 7.

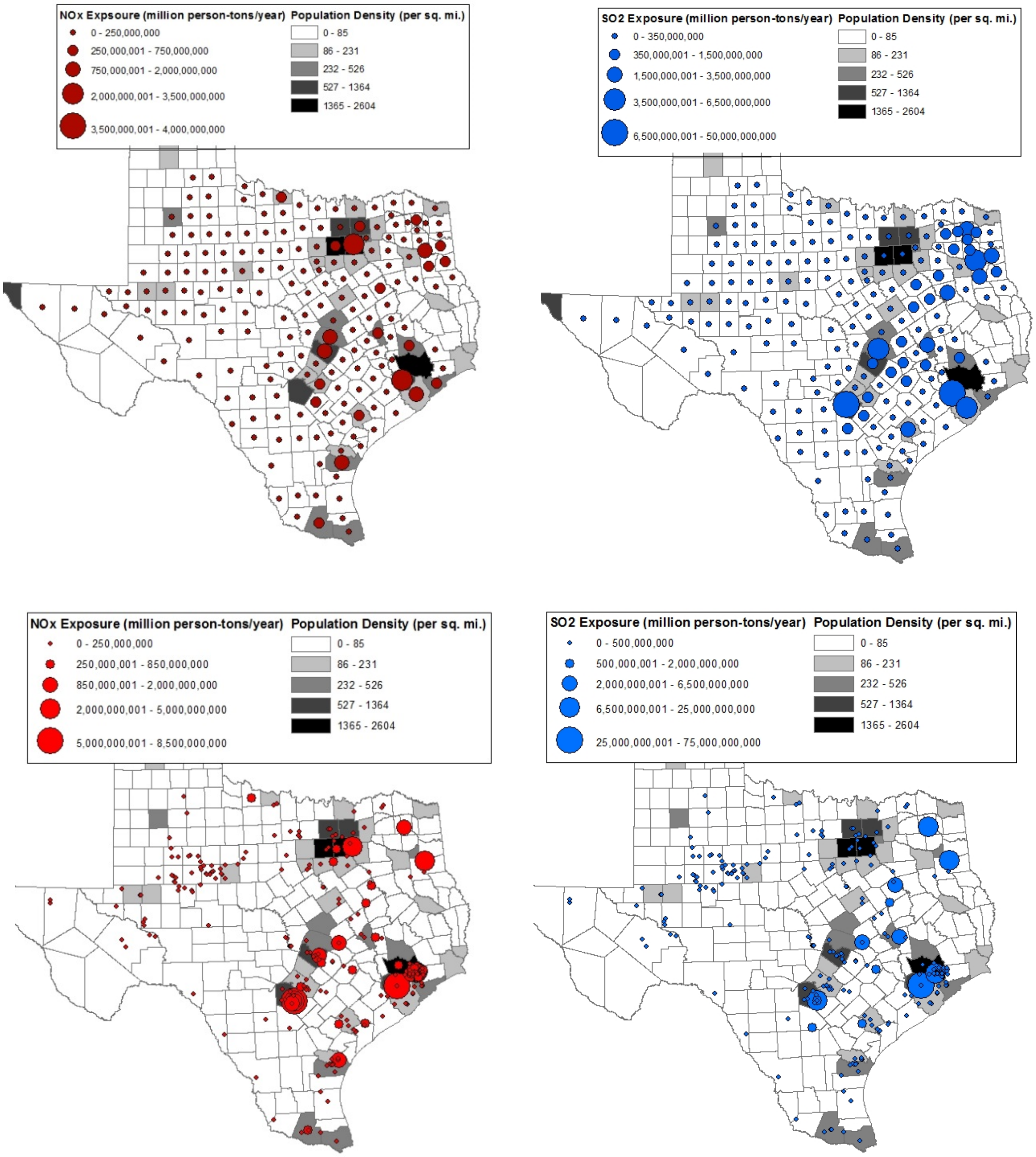

Figure 7: Total Emissions Exposure, by County for NOx, (top left) SO_2, (top right), and by Power Plant for NOx (bottom left) and SO_2 (bottom right), in millions of person-tons per year

For NO_x and SO_2 emissions levels via Texas' power plants, some of the highest exposure counties host Texas' most populous cities. These include Harris (for City of Houston), Travis (Austin), Bexar (San Antonio), and Dallas counties. In addition to these urban areas, many rural counties also emerge with high emissions levels; these include central-Texas counties such as Anderson and Brazos, as well as most of northeast Texas. These counties have much lower population densities than the metro areas, but show a disproportionate exposure rate than some nearby counties that do not contain a polluting power plant.

Milam, Fayette, Limestone, Freestone, Grimes, and Rusk counties are all home to major coal plants. While it is not surprising to see such high NO_x and SO_2 exposure rates in these locations, it is interesting to get a sense of the disproportionately higher rates there, versus those in Texas' much more densely populated areas. In other words, smaller populations living near the coal plants are subject to greater power-generation emissions exposure. Even with much higher population numbers in the cities, which have nearby EGUs, aggregate exposure rates are less than those surrounding highly-polluting power plants in Texas' rural areas. Of course, the details of these exposures are much more nuanced, reflecting more than basic proximity. Nevertheless, at this coarse scale of county-level resolution, it seems clear that EV's electricity use (mostly in the major cities) will be outsourcing emissions to more rural populations. This is most apparent with SO_2, while results for other pollutants suggest that urban populations are about as negatively affected as rural populations (in terms of the product of population and emissions tons: the actual epidemiology is much more complex, and holds more hazards for those exposed to higher levels of most pollutants).
This result supports the idea that some rural areas may be subjected to higher emissions from EV adoption, use, and charging in urban areas, but the regions with more vehicles are more likely to carry the burden of exposure. In other words, enough power plants operate in Texas's most populated regions that EVs are not shifting all or even most of their associated emissions impacts to outlying areas, though there are certainly cases where the shifts may be disproportionate. Figure 7 highlights how EV charging emissions may often affect less populated areas of Texas. Of course, CV users impose emissions externalities on occupants of the cars that follow them, and the pedestrians, cyclists, and school children that travel and play nearby. Without 100-percent clean transport technologies, one cannot avoid the issue of externalities and inequities in emissions impacts.

CONCLUSIONS

This analysis confirms an already well-known fact: electricity produced from coal-burning power plants (both newer generation and older generation) is generally much more polluting than that produced by power plants relying on natural gas and renewables. While EVs powered exclusively by the average coal-fired power plant in Texas's ERCOT grid (in year 2012) may produce around 3,200 times more SO_2 (per mile-traveled) than electrified miles powered exclusively by Texas' natural gas plants, their emissions rates of NO_x, CO, and VOCs are still significantly less than those of CVs. Also somewhat surprising are the air quality and GHG savings associated with natural gas plants (with emissions rates based on current ERCOT averages for natural gas plants), and the relatively constant emissions rates (and feedstock mix) of Texas's power plants across different levels of demand on most any day of the year. . Specifically, charging a PEV on the ERCOT grid with only coal plants in the mix results in over 14 times as much NO_x emissions, 3,200 times as much SO_2, nearly 10 times as much CO_2 and CO_2eq, 2.5 times as much PM_{10}, and VOCs, and nearly 80 times the N_2O – as compared to a grid powered only by natural gas plants. Of course, including a small share of biomass and renewables (including wind, hydroelectric, and solar power) is even more favorable than the natural gasz scenario. This result indicates that coal plants are drastically more polluting than other EV fuel sources, as shown in Table 5.

Overall, higher PEV shares in urban areas may help improve local air quality and help regions meet NAAQS for CO, N_2O, ozone, and PM (2.5 and 10), specifically. If, however, a region has any nearby coal plants impacting regional air quality, PEVs can create much more of an SO_2 (and thereby PM2.5[4]) problem for the region than CVs would. Since SO_2 emissions from coal plants (compared on a per-mile basis to CVs) are so relatively high, one should be cautious when using them to power any PEVs, especially in a place where coal emissions could be affecting large populations. All Texas counties are within NAAQS for SO_2, but several Midwest and East Coast counties are in nonattainment (EPA 2013), presumably from higher concentrations of coal plants, higher sulfur contents of their coal, and heavy industry in these areas. Though SO_2 emissions are not necessarily a present concern in Texas, greater PEV demands being met with more coal plants (in populated areas) could be problematic. Essentially, adding an electrified mile to a system that depends on coal power would be equivalent to adding 3,200 CV miles, in terms of SO_2 emissions. This is an interesting result, because even at their relatively small shares, PEVs using coal-based electricity will have very disproportionate SO_2 emissions impacts.

Pollution carries negative-externality costs, and these have been estimated in recent years. Given the significant difference in associated SO_2 emissions, and the high (estimated) cost of this pollution species, Table 8 calculations suggest that a PEV's emissions benefits may be lost (relative to the 2010 fleetwide average passenger car), if partly powered by coal (ERCOT's feedstock share is 25 percent, very typical of U.S. power production). Table 8's dollar totals assume that each vehicle drives 12,000 miles per year, and damage values (in dollars per ton of species) come from the U.S. NHTSA (2010) for criteria pollutants; social cost of carbon is based on Interagency Working Group estimates (2013). Table 8's costs per ton are somewhat higher than those found elsewhere (see, e.g., Fann et al. 2012), but provide a conservative accounting of the health and environmental impacts attributable to CVs and PEVs.

Table 8: Comparing the External Emissions Costs

		Emissions Externalities over 12,000 Annual Miles	
	Pollution Costs ($/metric Ton)	**2010 Avg. Passenger Car (Gasoline)**	**BEV using 2012 ERCOT Grid**
VOC	$1,280	$4.32	$0.03
NO_x	$5,217	$25.75	$10.64
PM_{10} (directly emitted)	$285,469	$116.29	$47.96
SO_2	$30,516	$2.82	$263.66
CO_2	$20	$94.49	$67.20
Subtotal Non-SO_2	--	$240.85	$125.83
Total (per 12,000 mi.)	--	**$243.67**	**$389.49**

[4] SO_2 condenses to form sulfate particles, an important component of PM2.5, and responsible for tens of thousands of premature deaths each year, just in the U.S. (Fann et al. 2013).

Note: Pollution costs per ton come from NHTSA (2010) and Interagency Working Group on Social Cost of Carbon (2013). Passenger car emissions rates assume 30 mi/h running speed, and come from MOVES rates, as provided in the Project Evaluation Toolkit (Kockelman et al. 2012).

It seems clear that an EV's impacts on SO_2 emissions should not be ignored, even if some regions use little coal (notably the U.S. West Coast), actual damage costs are debatable, and shares of renewable feedstocks are rising (roughly a percentage point each year) in many regions. While the non-SO_2 portions of battery-powered EV emissions are less than three-quarters that of a modern gasoline passenger car, including SO_2 increases electrified travel's emissions costs to roughly 1.6 times those of a conventional passenger car. Thus, a grid's power sources, specifically coal-fired plants, are extremely important for EV emissions and benefits (or costs).

Overall, this study illustrates how a higher share of efficient natural gas and renewables (including nuclear) can reduce electrified-mile emissions, relative to CV use and PEVs powered by coal plants or inefficient natural gas plants. However, a focus on air emissions ignores some other environmental consequences of power production. Simply turning away from coal sources is not without issues. For instance, nuclear power production and waste disposal carries safety and environmental contamination risks, and is a massive freshwater consumer (Gleick 1994). Natural gas may also be responsible for environmental issues, since hydraulic fracturing techniques require much water and may be degrading underground water stores (see, e.g., Osborn et al. [2011] and Entrekin et al. [2011]), while releasing large amounts of global-warming methane (Howarth et al. 2011). Even wind turbines, solar panels, and hydroelectric power are not immune from environmental damages: generators threaten certain migratory bird populations, solar panels require extensive land area that may disrupt animal habitats, and hydroelectric dams interrupt aquatic ecosystems. Effectively, there is no motorized-transport energy solution that enjoys truly negligible costs, has zero environmental impact, and can move our world's growing population billions of miles per day. However, solutions like electrified transport, with cleaner power sources, vehicles and batteries manufactured with less embodied emissions, greater use of non-motorized travel models, reliance on closer destinations as activity sites (to reduce travel distances), and more efficient power sources and vehicles can help reduce the local, regional, and global costs of our mobility desires, while improving the energy security situation of most nations.

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