AIR QUALITY IMPACTS OF ELECTRIC VEHICLE ADOPTION IN TEXAS

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Published in *Transportation Research Part D* 34: 208-218, 2015

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).

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.

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. This study aims to quantify some of these impacts, and provides a framework for informing local and regional air quality plans.

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 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.

EV Usage and Driving Behavior

EV use assumptions used here come from extensive GPS-based data of Nissan Leaf vehicle 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 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] Detailed summaries of these results are compiled by Nichols (2013).

Electric Vehicle Emissions Model

Average daily electricity demand (*D*) is assumed using the average distance traveled (29.7 mi/day) and battery efficiency rate (300 Wh/mi) for Nissan Leaf vehicles, from Ecotality (2013). This 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 PEVs 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.

[1] Quarters are defined as follows: Q1 January to March, Q2 April to June, Q3 July to September, Q4 October to December.

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.

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

$$E_t = D \times \frac{d_t}{\sum_t d_t}$$

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 PEV adoption scenarios, electrified-mile emissions are estimated. Emissions estimation becomes more complex here, 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 PEV 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).[2] 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:

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

[2] 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.

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*) 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 daily demand to determine average 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.

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 1. Table 1'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 1: 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.

Comparing different charging profiles indicates little difference between charging scenarios, as shown in Table 2. 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 2: 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 2'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.

Conventional Vehicle Emissions

Average PEV emissions were compared to those of four different CV types, as shown in Table 3, 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 3 (and developed for use in Kockelman et al.'s [2012] Project Evaluation Toolkit, for Texas applications). Table 3'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 3: 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
PEV 2012 Avg. ERCOT Mix	0.17	0.72	**0.014**	**0.15**	**0.002**	13.34	16.13	**280**
PEV 2012: 100% Coal	0.47	2.23	0.036	**0.43**	**0.005**	33.14	49.15	761
PEV 2012: 100% NG	**0.03**	**0.00**	**0.005**	**0.02**	**0.002**	6.12	0.63	**78**
PEV: 25% Increase in Renewables	**0.12**	0.54	**0.011**	**0.11**	**0.002**	10	12.1	**210**

Note: Bold indicates PEV 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 and CV driving. The most striking difference is the considerably higher SO_2 emissions from PEVs 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 PEV miles in all feedstock mix scenarios, yet overall CO_2 emissions are lower in most cases for PEVs (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 PEV passenger car is less pronounced, suggesting about a 20% increase for the PEV car, but still underscores the inherent inefficiency of using a PEV 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.

PEVs 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 PEV's PM_{10} emissions on the existing grid nearly equal those of the average gasoline car, and PEV'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 4: 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
PEV 2012 Avg. ERCOT Mix	0.17	0.72	**0.014**	**0.15**	**0.002**	13.34	16.13	**280**
PEV 2012: 100% Coal	0.47	2.23	0.036	**0.43**	**0.005**	33.14	49.15	761
PEV 2012: 100% NG	**0.03**	**0.00**	**0.005**	**0.02**	**0.002**	6.12	0.63	**78**
PEV: 25% Increase in Renewables	**0.12**	0.54	**0.011**	**0.11**	**0.002**	10	12.1	**210**

If CVs do achieve such emissions reductions, PEVs 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 1. Another source of such estimates is Michalek et al. (2011), who have estimated high embodied energy implications for EVs.

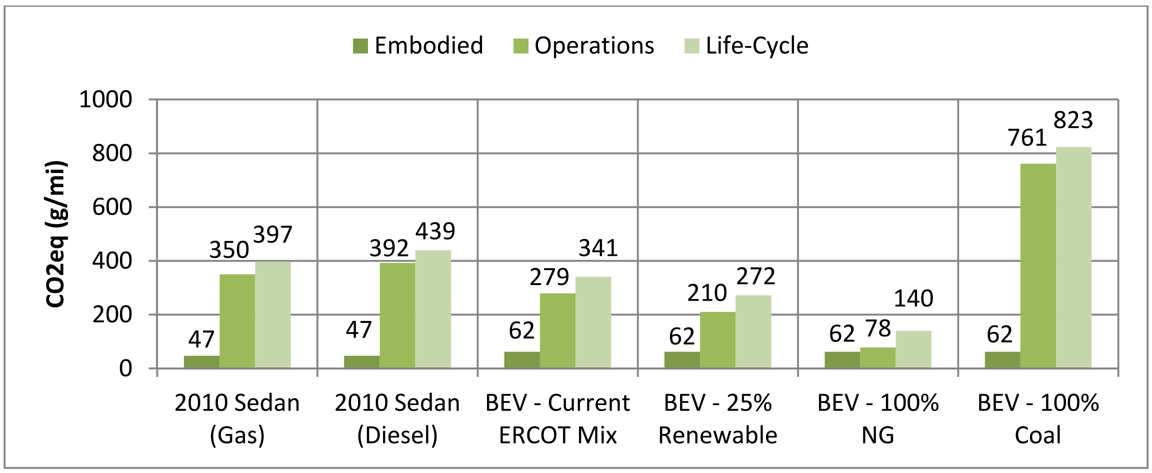

Figure 1: Life-Cycle CO_2eq Emissions of CVs vs. PEV Scenarios

This analysis suggests that most life-cycle energy for conventional vehicles, and PEVs fueled by coal, is from daily driving rather than from production phases. Although PEV 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 PEVs using the current mix. These results suggest that PEVs 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.

There is one emissions-species case studied here where PEVs, under any fuel mix scenario other than 100% renewables, perform worse than CVs; this is the case of SO_2 emissions. Figure 2 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).

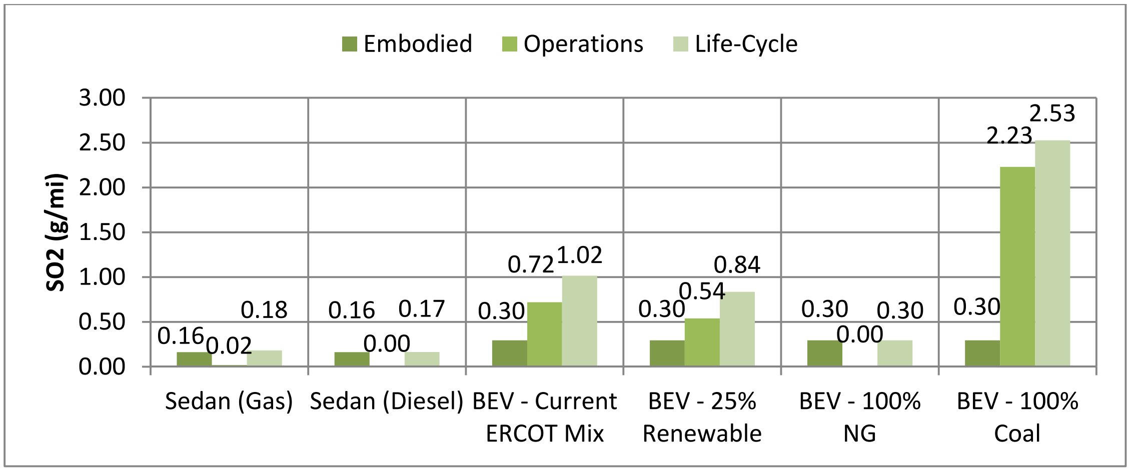

Figure 2: Life-Cycle SO_2 Emissions of CVs vs. PEV Scenarios

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 PEVs, 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 3’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 3.

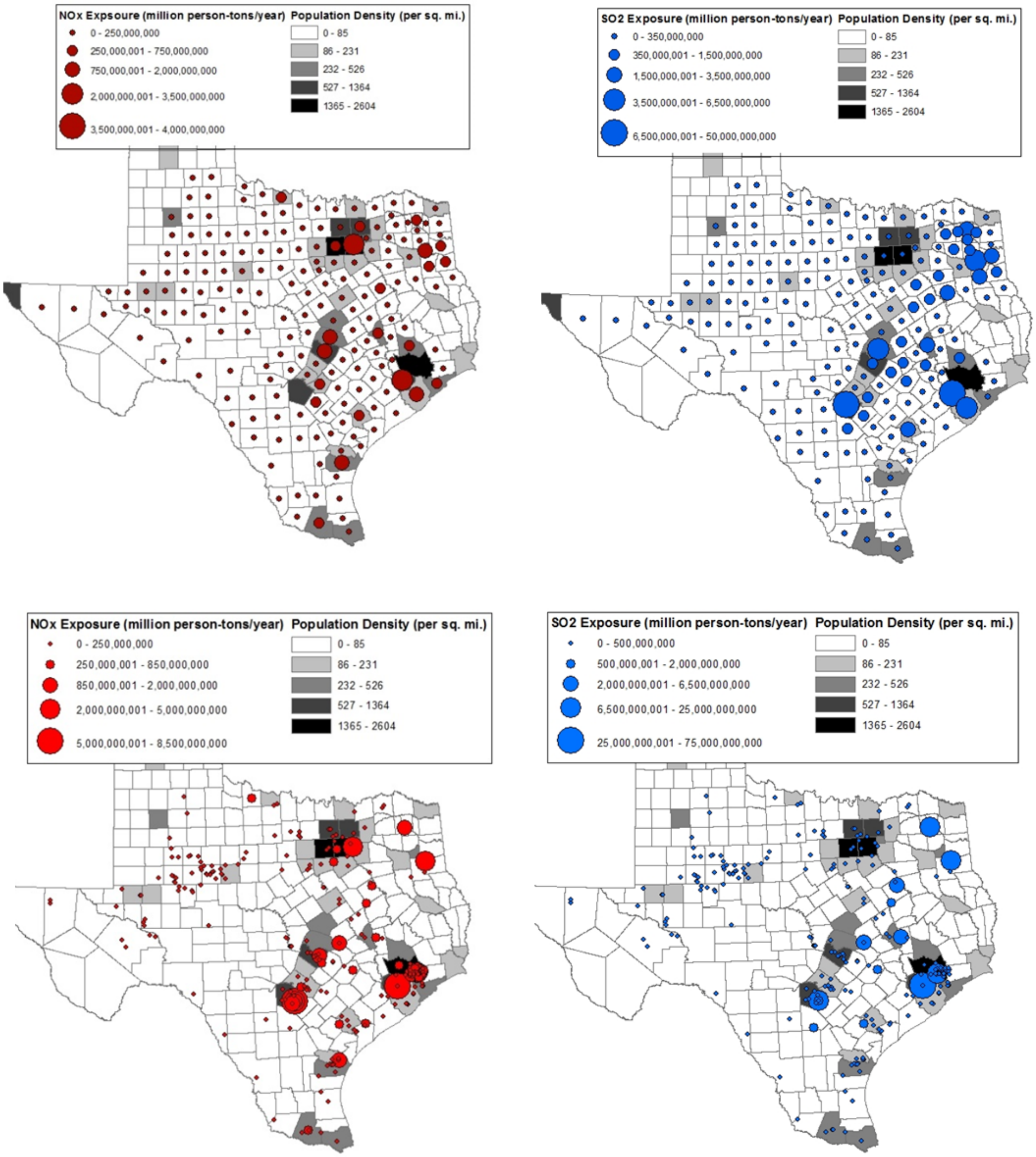

Figure 3: Total Emissions Exposure, by County for NOx, (top left) SO_2, (top right), and by Power Plant for NOx (bottom left) and SO_2 (bottom right), in millions of person-tons per year

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 3 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 gas scenario. This result indicates that coal plants are drastically more polluting than other EV fuel sources, as shown in Table 3.

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[3]) 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 5 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 5'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 5'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 5: Comparing the External Emissions Costs

		Emissions Externalities over 12,000 Annual Miles	
	Pollution Costs ($/metric Ton)	**2010 Avg. Passenger Car (Gasoline)**	**PEV 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**

[3] 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.

ACKNOWLEDGEMENTS

This project was funded by the Electric Vehicle Transportation and Electricity Convergence (EV-TEC) Center, a joint research program between the University of Texas at Austin, Texas A&M University, the National Science Foundation, and numerous corporate and governmental agencies. The authors appreciate Matt Reiter's careful review and content suggestions, and Annette Perrone's invaluable administrative and project management assistance.

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