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Marginal Emissions Factors for Electricity Generation in the Midcontinent ISO

Maninder P. S. Thind,[†] Elizabeth J. Wilson,[‡,§] Inês L. Azevedo,[∥] and Julian D. Marshall*[,†]

[†]Department of Civil and Environmental Engineering, University of Washington, Seattle, Washington United States

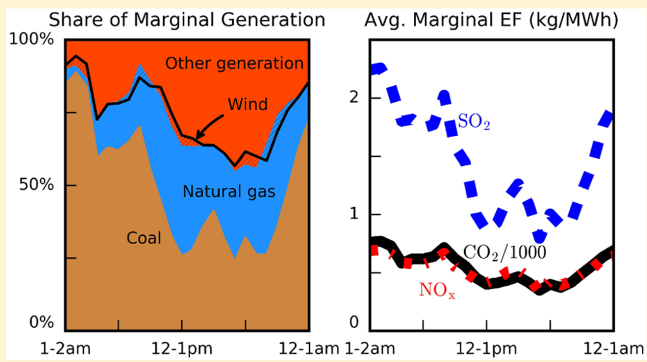
[‡]Humphrey School of Public Affairs, University of Minnesota, Minneapolis, Minnesota United States

[§]Environmental Studies, Dartmouth College, Hanover, New Hampshire United States

[∥]Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, Pennsylvania United States

Supporting Information

ABSTRACT: Environmental consequences of electricity generation are often determined using average emission factors. However, as different interventions are incrementally pursued in electricity systems, the resulting marginal change in emissions may differ from what one would predict based on system-average conditions. Here, we estimate average emission factors and marginal emission factors for CO_2, SO_2, and NO_x from fossil and nonfossil generators in the Midcontinent Independent System Operator (MISO) region during years 2007−2016. We analyze multiple spatial scales (all MISO; each of the 11 MISO states; each utility; each generator) and use MISO data to characterize differences between the two emission factors (average; marginal). We also explore temporal trends in emissions factors by hour, day, month, and year, as well as the differences that arise from including only fossil generators versus total generation. We find, for example, that marginal emission factors are generally higher during late-night and early morning compared to afternoons. Overall, in MISO, average emission factors are generally higher than marginal estimates (typical difference: ∼20%). This means that the true environmental benefit of an energy efficiency program may be ∼20% smaller than anticipated if one were to use average emissions factors. Our analysis can usefully be extended to other regions to support effective near-term technical, policy and investment decisions based on marginal rather than only average emission factors.



1. INTRODUCTION

In the United States, electricity generation is a major contributor to air pollution, with important consequences for health, the environment, and climate. The U.S. Environmental Protection Agency (EPA) estimates that in 2014, electricity generating units (EGUs) contributed 37% of CO_2, 67% of SO_2, 13% of NO_x, and 3% of primary $PM_{2.5}$ nation-wide emissions.[1,2] SO_x and NO_x emissions from EGUs contribute to secondary $PM_{2.5}$ formation, adding to the health and environmental consequences of EGUs. In 2014, coal-fired EGUs alone generated ∼39% of the electricity in the U.S., and contributed to 77%, 97%, 86%, and 81%, respectively, of CO_2, SO_2, NO_x, and $PM_{2.5}$ total electricity emissions.[1,3] Those pollutants contribute to acid rain, climate change, regional haze, crop damage, and health impacts from ambient air pollution.[4]

There are multiple approaches to estimating power plant emissions.[5] Different methods and data sources can generate substantially different estimates—an important consideration for environmental policy. A simple and straightforward approach is to calculate average emissions factors (EFs) for a region and time frame as the ratio between total emissions and total electricity generated. Another approach is to model marginal EFs based on bid-dispatch simulations of electricity generators;[6−11] such models use costs and engineering constraints to predict which EGU would increase/decrease output if the total energy demand at that time were marginally higher/lower. The degree of sophistication of these models varies. Models such as Integrated Planning Model (IPM), PROMOD, Electric Generation Expansion Analysis System (EGEAS) and PLEXOS are proprietary, complex, often provide little flexibility, and are time-consuming to run; they require substantial input data, and like any model depend on assumptions and simplifications necessary to simulate a complex system.[12−16] Other approaches include the Fuel Type Assumed (FTA) method, Locational Marginal Price (LMP) based approaches, and machine learning algorithms.[17−20] Here, we use an empirical approach for estimating average EF (AEF) and average marginal EF (AMEF). Our approach, which was described in Siler-Evans et al. (2012),[21] is

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distinct in using data (historical observations) rather than models to estimate marginal EFs. The approach of using historical data has been applied in other studies as well.[22−25] EFs calculated using historical data are most appropriate for short to medium term analysis in electricity system, and are less appropriate for long-term predictions for which fundamental aspects of the electricity system (e.g., fuel mix; infrastructure) may shift. Several applications of marginal emissions and impact factors have been used to determine the emissions saving and damage reductions associated with interventions in the electricity sector, such as solar and wind,[26,27] energy efficient buildings,[28,29] storage,[30] and vehicle charging,[31,32] and wastewater treatment from coal power plants.[33]

While several studies have investigated average and marginal EF,[7−9,19,21,34,35] only one prior study has implemented the empirical approach employed here: Siler-Evans et al. (2012)[21] calculated AEF and AMEFs for the U.S. electricity system and for the eight North American Electric Reliability Corporation (NERC) regions. Those authors recommend that the method be applied to Regional Transmission Organizations (RTOs) rather than NERC regions, since RTOs provide a better representation of electricity dispatch; our approach follows that suggestion. We build on the Siler-Evans et al. (2012)[21] research, extending it in several ways: (1) We focus on an RTO rather than NERC regions. RTOs use bid-based markets to determine economic dispatch, and so are an appropriate scale for our analyses. (2) Siler-Evans et al. (2012)[21] consider fossil generation as proxy for total generation. That aspect is a limitation of their approach; with increasing amounts of renewables in the grid, renewables may be at the margin for some hours or levels of demand. We instead use total MISO generation (rather than fossil-only generation) when calculating EFs. (3) By focusing on a single RTO, we are able to assess with greater detail EFs's variability in time and space, thereby lending new insights into the environmental impacts of electricity generation. (4) We explore how EFs may vary by state, corporation, fuel-type, and EGU.

Average versus marginal EFs may differ for many reasons. In general, at a given time, the mix of fuels for the EGUs at the margin—that is, the last few units that will meet demand—may differ from the average electricity mix in that hour. Furthermore, for a single EGU, AEF, and AMEF may differ because the boiler is ramping up or down, or because the efficiency of emission control technologies may depend on the EGU's power output.

Our results for MISO, years 2007−2013, reveal that AMEFs are often lower than the respective AEFs. The consequences of this finding for policy includes, for example, that the true emission reduction attributable to an energy efficiency program may be lower than the one a decision maker would assume using AEFs. Similarly, this result would indicate that an efficiency program may be less cost-effective than anticipated (since cost-effectiveness metrics are often computed as the ratio between the cost of the program and the emissions saved).

2. MATERIALS AND METHODS

Here, we employ an empirical approach for estimating AEF and AMEF for the Midcontinent Independent System Operator (MISO). MISO is one of the seven U.S. RTOs. MISO includes 15 U.S. states, and serves ∼42 million people (13% of the U.S. population). In 2015, MISO included 176 600 MW of electric capacity, generating ∼667 800 GWh (∼16% of the U.S. total electricity generation). In the Supporting Information (SI), we provide the generation statistics for MISO for years 2007 through 2016 (SI Figure S1).

The geography of MISO changed in 2014: prior to 2014, MISO constituted 11 upper Midwest states and was called "Midwest ISO". In 2014, a south region (four additional states; see maps in SI Figure S2) was integrated to form "Midcontinent ISO". For geographic consistency, most results presented here are only for years 2007−2013; that approach provides an assessment that includes well-defined and consistent regional boundaries. Results for years 2014−2016, which include EGUs in the new regional boundaries, are in section 1 of the SI (Figure S3 and Table S1).

We use emission data from the Continuous Emissions Monitoring System (CEMS) database from the U.S. EPA.[36] CEMS provides hourly emissions of CO_2, SO_2, and NO_x, and energy generation for generators with nameplate capacity of 25 MW or larger. We complement this information with MISO databases that provide hourly imports, exports, total actual load, and wind generation.[37] Net imports account for ∼6% of the total demand in MISO. The share for "other" generation sources (nuclear, hydroelectricity, and other renewable generation) is calculated by subtracting fossil and wind generation from total generation.

We calculate two EFs for a given time period or geography: AEFs and AMEFs. AEFs are the summation of hourly emissions (E_T) divided by the summation of hourly generation (G_T) for that time period and geography.

Marginal EFs vary by time and geography; AMEF represents the average of the marginal EF for a certain time period and over some spatial extent. AMEF are computed by calculating the hourly change in emissions (ΔE) and change in generation (ΔG), for each time step. Then, a linear regression is fitted to identify the relationship between those two variables (the change in emissions and in generation). The slope of the linear regression (β_o) between those two values is the AMEF.

In addition to estimating AEF and AMEF for MISO during 2007−2016, we also investigate spatial and temporal variability in EFs at multiple temporal and spatial scales. We do so for the following scenarios: the 11 Midwest states in MISO; all corporations owning one or more generators in a case-study state (Minnesota) and, as a separate analysis, in the entire MISO (in SI); and, at the level of individual EGUs. We also estimate AEFs and AMEFs by fuel type, for coal and for natural gas, to understand the average marginal response of fuel-specific generators to changes in system demand. In general, we employ total generation when estimating AEFs and AMEFs. One exception, caused by limited data availability, is that state and utility-level EFs include fossil-only generation as a proxy for total generation. Net imports are subtracted from MISO total load to obtain net generation. Electricity exchanges and trading at the state and utility scales are not considered here because they are tracked and available only at the RTO level. Fuel specific AMEFs are calculated by aggregating emissions by fuel type at each time step and performing regression between change in fuel-specific emissions and change in total generation. For each EGU bidding in the MISO grid, we calculate AMEFs via regression between unit-specific hourly emissions and gross generation output. Coal and natural gas EGUs constitute most of the units that bid in MISO and hence are a focus of our analysis.

We also explore trends in AEFs and AMEFs in the MISO region as a function of total system demand. To do so, we bin the data from years 2007 through 2013 into 20 demand level

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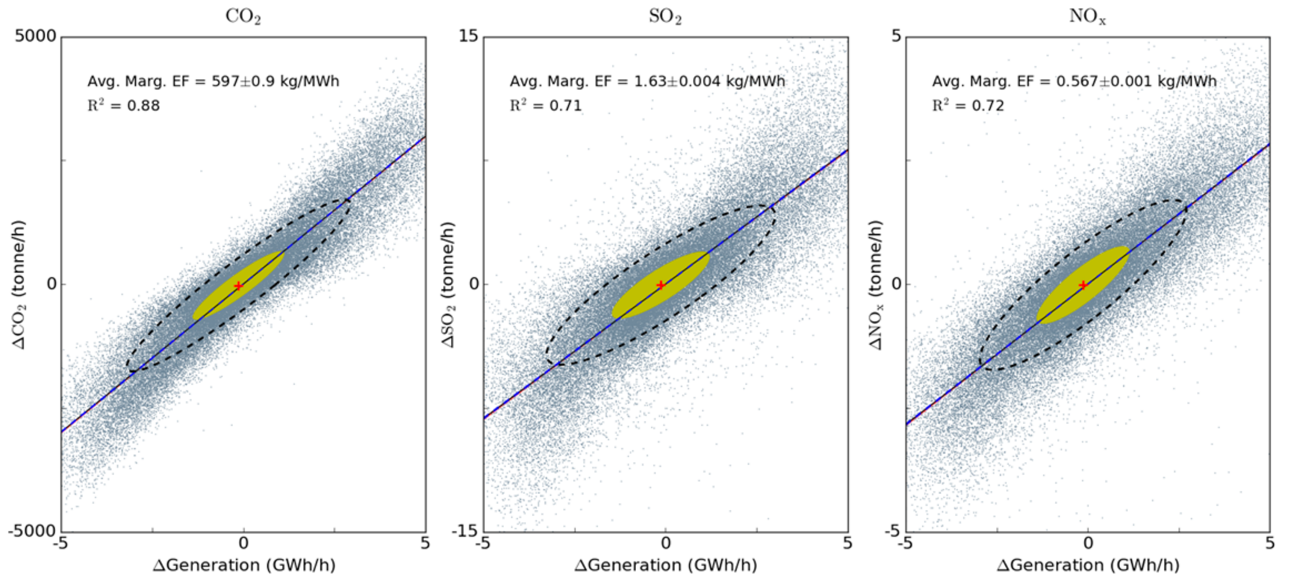

Figure 1. Linear regression for hourly changes in power generation and pollutant emissions, for Midcontinent ISO, years 2007 to 2013. Each dot represents a 1 h difference. We also show the median value (red icon), the interquartile ellipse (yellow) and P10−P90 ellipse (dashed line), the best-fit line (black line), and 95% confidence intervals on the best-fit line (dashed blue lines, nearly indistinguishable from the best-fit line).

bins. Each bin contains 5% of the data occurring at lowest to highest system demand hours. Separate regressions of ΔFuel Generation vs ΔTotal Generation are then performed for each bin. We also analyze trends in AEFs and AMEFs temporally by time-of-day, day-of-week, month and year (for years 2007 to 2016). To assess the differences between AEF and AMEF, we calculate their relative difference as

$$\%\text{difference} = \left(\frac{\text{AMEF} - \text{AEF}}{\text{AEF}}\right) \times 100$$

3. RESULTS

3.1. Comparison of AEF and AMEFs.

Emissions Estimates for MISO. Figure 1 presents data for years 2007−2013. Each data-point is an hourly change in MISO total pollutant emissions and power generation. The slope of the best-fit line is the AMEF. Figure 1 also displays the median data-point (red icon), the IQR ellipse (centered at the median data-point, displaying 25th and 75th percentiles parallel and perpendicular to the best-fit line; yellow ellipse), and the P10−P90 ellipse (centered at the median data-point, displaying 10th and 90th percentiles parallel and perpendicular to the best-fit line; dashed line). As expected, for data in Figure 1, ∼25% of the data-points are inside the IQR ellipse, ∼60% are inside the P10−P90 ellipse.

Table 1 summarizes the results displayed in Figure 1. SI Figure S3 and Table S1 provides the results for years 2014−2016 (i.e., after the change in geography). Overall, and among pollutants, we find that AMEFs are 17%−22% lower than the respective AEF. This general pattern holds across pollutants and years (see SI Table S2).

Table 1. Comparison between AEF and AMEF Estimates for the MISO Region Using Data from 2007 to 2013

pollutant	AEF (kg/MWh)	AMEF (kg/MWh)	EFs % Difference
CO_2	739	597	−19%
SO_2	1.97	1.63	−17%
NO_x	0.727	0.567	−22%

For comparison, we also computed these estimates when including only fossil generation (which was the approach taken in Siler-Evans et al. (2012)[21]). When doing so, we find that the differences between EFs remain consistent (AMEFs 15%−19% lower than the respective AEF), but the AEFs are ∼22% greater and AMEFs are ∼27% greater than their values calculated using change in total generation.

We also estimate AEFs and AMEFs by fuel type, which we report in the SI, Tables S3, S4, and S5. We find that relative to other fuels, the AMEFs from coal-fired generators are generally closer to emission factors for entire MISO region. This result is likely because the average share of marginal generation from the coal fleet is greater than the natural gas fleet (∼57% coal vs ∼21% natural gas). For emissions from coal generators only, the AMEF is 28% [CO_2], 18% [SO_2], and 27% [NO_x] lower than AEF. For natural gas generators only, the AMEF is 274% [CO_2], 78% [SO_2], and 182% [NO_x] higher than AEF.

State Level Estimates. State Implementation Plans (SIPs) often require an accurate metric to assess emission benefits from different energy efficiency strategies. We have calculated AEF and AMEF for the state boundaries within MISO, as shown in Figure 2. For this portion of the analysis, we rely on total fossil generation when computing the emissions factors because there is no total generation data by state at the hourly level. For each state, this analysis considers only emissions and generation occurring within that state. We find that in most cases, AMEFs are lower than AEFs (which is consistent with results given above). Differences between AEF and AMEF are larger for states that have a large portion of their generation provided by natural gas (see SI Figure S4); not surprisingly, natural gas tends to be more on the margin in those states. Correlations among CO_2 AMEF, SO_2 AMEF, and NO_x AMEF are shown in SI Figure S5.

Utility Level Estimates. We compute separate EFs for utilities that operate in MISO. At the utility scale, AEFs and AMEFs are important as they may be used to inform utilities' strategies to reduce their emissions (for example, on decisions

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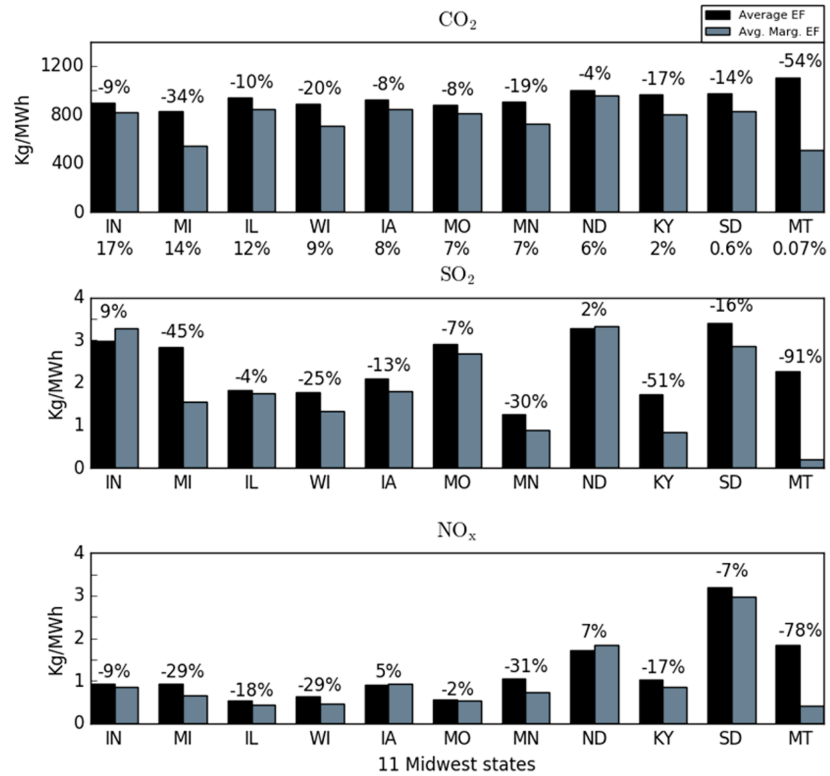

Figure 2. AEF and AMEF by state for CO_2, SO_2 and NO_x for years 2007−2013. The percentages reported show the relative difference between AEF and AMEF (positive values mean AMEF > AEF). States are displayed from highest to lowest electricity generation share of MISO's total generation. The electricity generation share for each state is shown along the *x*-axis for the CO_2 plot. In combination, fossil generation from these states accounted for 82% of MISO total generation.

of how to allocate emission allowances under cap and trade programs, or for monitoring and evaluation of climate mitigation or other emission reduction programs). Here, as a case-study, we calculate AEF and AMEF for utilities operating generators in Minnesota in year 2012. Differences between AEF and AMEFs for all utilities bidding in MISO in the year 2012 are presented in SI Figure S6. Minnesota's emission reduction goals include a 40% reduction in CO_2 emission rate; we use year 2012 as an illustrative example given that it was the baseline year for U.S. EPA's former Clean Power Plan rule. Here too, owing to limitations in data availability, we employ the approach from Siler-Evans et al. (2012), and use total fossil generation instead of total generation. In Figure 3 we provide the resulting estimates for each utility operating generators in Minnesota. In this figure, the Minnesota Municipal Power Agency is atypical in that it has slightly negative AMEF for NO_x. It has the only must-run combined cycle natural gas unit with a large nameplate capacity (334.5 MW) and with installed NO_x control equipment. Nonlinear emission changes attributable to shifting usage of NO_x control equipment could explain the negative AMEF for NO_x.

Generator Level Analysis. We calculate AEF and AMEF for each generator bidding in MISO during years 2007 to 2013, which are shown in Figure 4. Over this time period, on average, 273 natural gas generators and 219 coal generators bid into MISO each year. In most cases, we find (consistent with results given above,) that AMEFs are smaller than AEFs: median differences between AEFs and AMEFs for coal are −4.9% for CO_2, −0.1% for SO_2, and −3.3% for NO_x; for natural gas, median differences are −6.3% for CO_2, −5.5% for SO_2 and −10.0% for NO_x. The AMEF-AEF percent difference is less than −20% (i.e., is more-negative than −20%) for CO_2 for 5% of coal generators and 6% of natural gas generators, for SO_2 for 7% (coal) and 10% (natural gas) generators, and for NO_x for 27% (coal) and 29% (natural gas) generators. Those results emphasize that there can be noteworthy differences between AEF and AMEF estimates when applied at the generator level.

On average, we find that AMEF-AEF differences are larger for SO_2 and NO_x than for CO_2 and are larger for coal than for natural gas. This result may reflect the nature of SO_2 and NO_x emission control equipment. Further analysis (see SI section 4) reveals that for coal generators, the AEF and AMEF difference for CO_2 is larger for smaller generators than for larger generators (SI Figures S11 and S13). However, the reverse holds for natural gas (SI Figures S12 and S14). This observation likely reflects generator characteristics such as heat rate, capacity factor and age (SI Figure S15). An explanation for the coal units could be that old smaller (i.e., low capacity factor) units run at higher heat rates compared to their design heat rates, whereas new larger units (high capacity factor) typically run at heat rates at or below their design heat rates. As generators age, their heat rates degrade and the smaller units tend to cycle and follow load more. Hence, coal units with low capacity factors have higher AEF, and the larger difference between metrics. Additionally, EFs seem to be inversely correlated with share of electricity (see SI Figures S16 and S17), suggesting that share of electricity is greater for lower EF units than for higher EF units.

3.2. AEFs and AMEFs by System Demand. In Figure 5 (A and B), we show the share of average and average marginal fuel source with respect to total generation in MISO. Coal is the dominant marginal fuel at low demand hours; natural gas is

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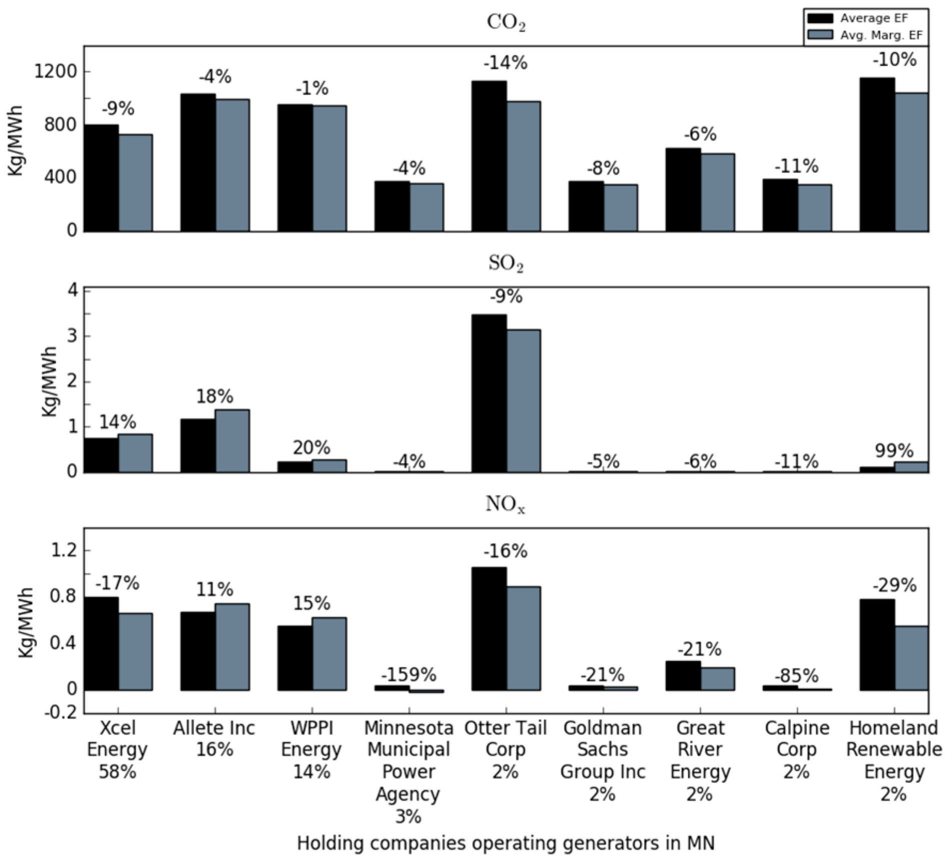

Figure 3. AEFs and AMEFs for utilities operating EGUs in Minnesota in 2012 that have a generation share >1%. The percentages inside the figure represent the relative difference between AEF and AMEF (positive values indicate AMEF > AEF). *X*-axis percentages (e.g., 58% for Xcel Energy) indicate percentage generation share of Minnesota's total fossil generation; utilities are listed in order of that percentage.

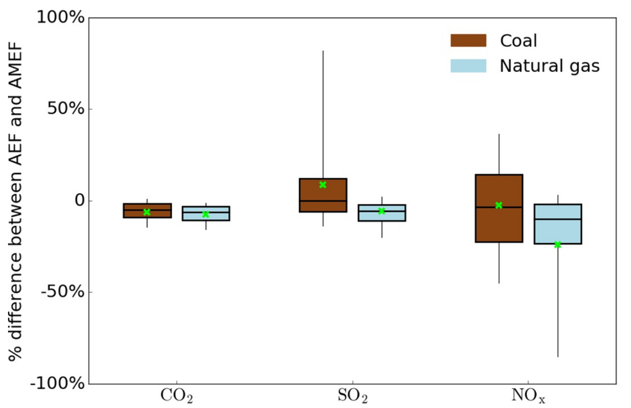

Figure 4. Boxplot showing distribution of EF differences among coal units (n = 219, average per year, 2007−2013) and natural gas units (n = 273 on average). Mean value is shown as green icon.

the dominant marginal fuel at high demand hours. The share of other fossil fuels to marginal generation is minor. Nuclear is generally not on the margin (which is consistent with output being ∼ constant and/or with changes in output being relatively uncorrelated with changes in demand). The share of generation from wind is greater during low demand hours (since average wind speeds in the Midwest are higher at night than during the day) than high demand hours, and the marginal generation from wind is negative (i.e., on average, wind generation decreases in hours when system total generation increases) during low demand hours. Two possible reasons for negative marginal generation couldbe (1) load curtailment or (2) a decrease in generation because of less wind. We do not have hourly curtailment data needed to rigorously investigate the reason behind negative marginal generation. However, curtailment appears not to be a large issue for MISO: a U.S. Department of Energy report[38] estimates wind curtailment in MISO at <6% of potential wind energy generation. Curtailment was a larger issue for some other grids, notably the ERCOT grid, which experienced >15% curtailment in 2009 (but steps taken to address the issue reduced wind curtailment, to only 1% in 2015). Recent MISO programs have strived to make wind dispatchable like other fuels via, e.g., the Dispatchable Intermittent Resources program.[39,40]

Parts C and D of Figure 5 shows how AEF and AMEFs for CO_2, SO_2 and NO_x vary with MISO total generation. NO_x AMEF is relatively constant across demand. SI Figure S18 shows similar plot for year 2008 (wind data for year 2007 is not available) and 2013 for comparison; there is not much change in marginal generation from coal over the course of 6 years, and average share of wind has increased but its contribution to marginal load decreased substantially in the year 2013.

3.3. Temporal Analysis. We explore variation of AMEFs (and AEF; SI Figure S19) by time of day, days of week, month and year (Figure 6). AMEF are higher-than-average during late-night and early morning hours when electricity demand is lower and coal is more often on the margin: AMEF is about 73% [CO_2], 125% [SO_2], and 55% [NO_x] higher at midnight compared to noon. The AMEFs are higher on the weekends compared to weekdays. AMEFs are highest in spring and fall,

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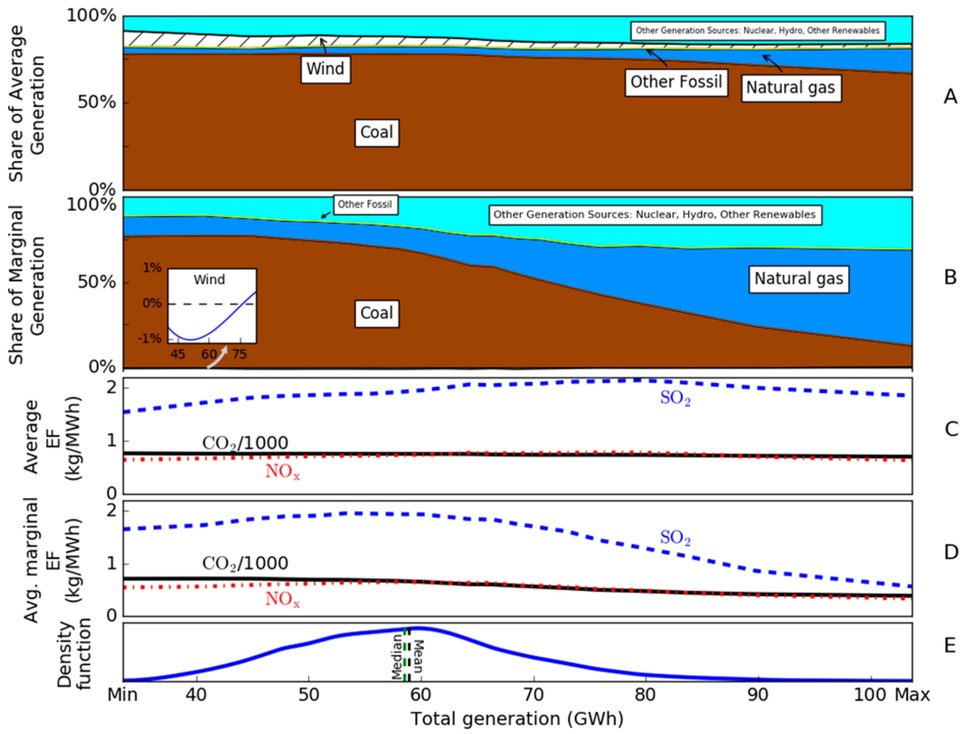

Figure 5. (A) Average generation by fuel. (B) Average marginal generation by fuel. (C) AEFs as a function of total generation. (D) AMEFs as a function of total generation. (E) Kernel density distribution for total generation. All results are for MISO, for all data-points during years 2007−2013.

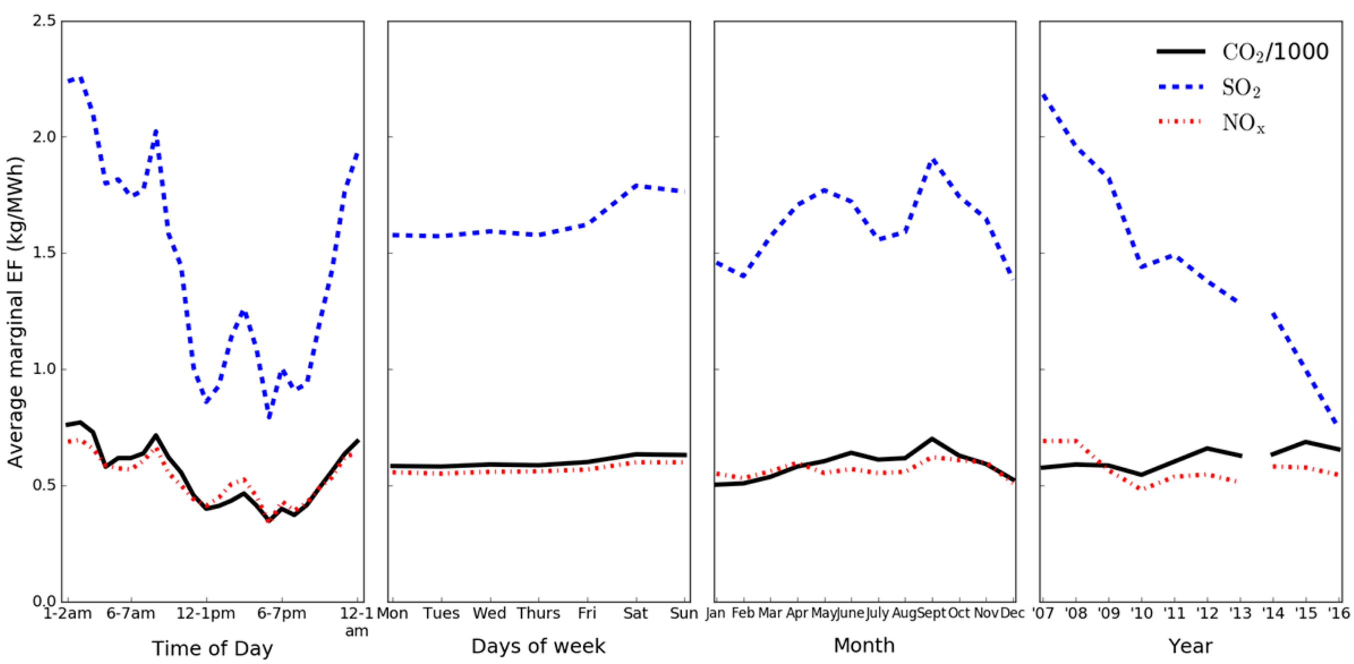

Figure 6. Time of day, days of week, and monthly trends in AMEFs for years 2007 through 2013. Yearly trends shown here for 2007 through 2016. The discontinuity in the yearly plot is to highlight the change of MISO geography after 2013.

when demand is low and coal is more often on the margin. Time-of-day trends are more pronounced in summer (SI Figure S20). Fuel-specific AEF and AMEFs by time-of-day are in SI Figure S21 and SI Table S6. From 2007 through 2013, AMEF for SO_2 decreased by 41%; changes were smaller for NO_x (26% decrease) and CO_2 (9% increase). From 2014 to 2016, AMEF for SO_2 decreased by 40%, NO_x decreased by 6% and CO_2 increased by 3%. Reduction in SO_2 and NO_x can be attributed in part to U.S. EPA regulations to reduce air pollution from the electricity sector. AEFs do not show pronounced variations by time of day, day of week and months (SI Figure S19). As seen in Figure 6, average MISO AMEFs were, for SO_2, lower after 2013 than before 2013; for CO_2, AMEFs were slightly higher after 2013 than before; for NO_x, they were mostly unchanged.

4. DISCUSSION

We investigated differences between AEF and AMEFs at different spatial and temporal scales for MISO. In general, AEFs

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tend to be larger than AMEFs, and thus may overestimate emission impacts from interventions in the power sector, relative to using AMEFs.

The deployment of renewable energy sources such as wind and solar will help reduce emissions by displacing energy from fossil-fired generators. However, if a decision-maker uses AEF to understand the current contribution of renewables or other interventions in the electricity system, she will likely overestimate the emission benefits that are derived from such interventions. As noted above, for MISO, if emission-reduction benefits (e.g., from wind or solar generation, or from energy efficiency programs) are calculated using AEFs, results here suggest that the benefits are on average overestimated by 19% for CO_2, 17% for SO_2 and 22% for NO_x. Those values vary by time-of-day, fuel, company, and state. Results presented here could help energy efficiency programs become more cost-effective, for example, by consideration of how AMEF varies in time and space.

We show that AMEFs are higher during early morning and late evening hours, times of day when electricity demand is usually low and, historically for the Midwest, when wind energy is abundant. Further harnessing of the wind potential during these hours could provide substantial emission reductions and is of great importance for strategies such as Active Power Controls (APC)[41] for efficiently harnessing wind energy during those times. Further, following Siler-Evans et al. (2012),[21] we calculated the daytime (8 am to 5 pm) and nighttime (7 pm to 7 am) AMEFs and compared them to system AMEF and AEF; we find that AEFs overestimate AMEFs by ~35% during daytime and by ~20% during nighttime (SI Table S7). For AMEF, differences between nighttime-average and daytime-average are ~14%.

This paper advances current understanding in a few key ways. We show that estimating recent AMEFs can be done using data rather than models. Siler-Evans et al. (2012)[21] and Graff Zivin et al. (2014)[24] looked at the temporal and spatial differences between AEFs and AMEFs for NERC regions. We adopted Siler-Evans et al. (2012)'s recommendation of focusing on RTOs, and in doing so uncovered important differences between AEF and AMEFs by time and geography (by state, corporation, and individual EGUs). In most cases, our analyses were based on total generation rather than using fossil generation as a proxy for total generation (exceptions include state and utility analyses, for which data limitations forced us to use fossil generation as a proxy for total generation). Electricity trading at the state and utility level could impact state and utility emission factor estimates,[42−44] but is not explicitly incorporated here.

Multiple methods exist for estimating AMEFs. Our approach has the advantage of being based on empirical data rather than models. On the other hand, that means it may be inappropriate to use findings here unmodified if considering major shifts in the electricity infrastructure. Since results presented here are based on historical data, they likely would not be directly applicable for predicting long-term changes in the electricity grid.

Coal is frequently the marginal fuel source, especially during low-demand hours; it is not merely a base-load fuel that sits apart from marginal generation. In MISO, coal generators operate on margin and follow the load profile. In the future, if MISO continues to shift away from coal, that aspect could change.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.7b03047.

Map of MISO region and fuel resource mix by years, MISO regional emission factors and differences by year, fuel type and year, statistics of generator EF differences (using ±5% and ±10% range) for combined years and by each year, temporal trends in AEFs and AMEFs, AMEFs by season (PDF)

■ AUTHOR INFORMATION

Corresponding Author

*Phone: (206) 685-2591; e-mail: jdmarsh@uw.edu.

ORCID

Maninder P. S. Thind: 0000-0003-3306-1507

Notes

The authors declare no competing financial interest.

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■ REFERENCES

(1) *2014 National Emissions Inventory (NEI) Data*; U.S. Environmental Protection Agency: Washington, DC, 2016. https://www.epa.gov/air-emissions-inventories/2014-national-emissions-inventory-nei-data (accessed 18 December 2016).

(2) *Overview of Greenhouse Gases*; U.S. Environmental Protection Agency: Washington, DC, 2016. https://www.epa.gov/ghgemissions/overview-greenhouse-gases (accessed 12.18.2016).

(3) *Sources of Greenhouse Gas Emissions*; U.S. Environmental Protection Agency: Washington, DC, 2016. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions#electricity (accessed 18 December 2016).

(4) Seinfeld, J. H.; Pandis, S. N.*Atmospheric Chemistry and Physics: From Air Pollution to Climate Change*, 2nd, ed.; John Wiley & Sons, Inc.: Hoboken, NJ, 2006.

(5) Ryan, N. A.; Johnson, J. X.; Keoleian, G. A. Comparative Assessment of Models and Methods to Calculate Grid Electricity Emissions. *Environ. Sci. Technol.* **2016**, *50* (17), 8937−8953.

(6) *Environmental Impacts of Wind-Energy Projects; National Research Council*; National Academies Press: Washington, D.C, 2007; https://www.nap.edu/catalog/11935/environmental-impacts-of-wind-energy-projects (accessed 18 February 2017).

(7) Marnay, C.; Fisher, D.; Murtishaw, S.; Phadke, A.; Price, L.; Sathaye, J. *Estimating Carbon Dioxide Emissions Factors for the*

California Electric Power Sector; Lawrence Berkeley National Laboratory report LBNL-49945: Berkeley, CA, 2002.

(8) *2003 NEPOOL Marginal Emission Rate Analysis*; ISO New England Inc., December 2004; https://www.iso-ne.com/static-assets/documents/genrtion_resrcs/reports/emission/Marginal_Emissions_Analysis_2003.pdf.

(9) Zheng, Z.; Han, F.; Li, F.; Zhu, J. Assessment of Marginal Emissions Factor in Power Systems Under Ramp-Rate Constraints. *CSEE J. Pow. Ener. Sys* **2015**, *1* (4), 37−49.

(10) Bettle, R.; Pout, C. H.; Hitchin, E. R. Interactions Between Electricity-Saving Measures and Carbon Emissions from Power Generation in England and Wales. *Energy Policy* **2006**, *34*, 3434−3446.

(11) Voorspools, K. R.; D'haeseleer, W. D. An Evaluation Method for Calculating the Emission Responsibility of Specific Electric Applications. *Energy Policy* **2000**, *28*, 967−980.

(12) *Clean Air Markets - Power Sector Modeling*; U.S. Environmental Protection Agency: Washington, DC, 2016; https://www.epa.gov/airmarkets/clean-air-markets-power-sector-modeling (accessed 11 November 2017).

(13) *MTEP16: MISO Transmission Expansion Plan*; Midcontinent Independent System Operator, Inc: Carmel, IN, 2017; https://www.misoenergy.org/Library/Repository/Study/MTEP/MTEP16/MTEP16%20Full%20Report.pdf.

(14) *Analysis of EPA's Proposal to Reduce CO2 Emissions from Existing Electric Generating Units*; Midcontinent Independent System Operator, Inc.: Carmel, IN, 2017; https://www.misoenergy.org/Library/Repository/Communication%20Material/EPA%20Regulations/AnalysisofEPAsProposaltoReduceCO2EmissionsfromExistingElectricGeneratingUnits.pdf.

(15) Brinkman, G.; Jorgenson, J.; Ehlen, A.; Caldwell, J. *Low Carbon Grid Study: Analysis of a 50% Emission Reduction in California; NREL/TP-6A20−64884*; National Renewable Energy Laboratory (NREL): Golden, CO, January 2016; http://www.nrel.gov/docs/fy16osti/64884.pdf.

(16) Foley, A.; Tyther, B.; Calnan, P.; Ó Gallachóir, B. Impacts of Electric Vehicle Charging Under Electricity Market Operations. *Appl. Energy* **2013**, *101*, 93−102.

(17) *2013 ISO New England Electric Generator Air Emissions Report*; ISO New England Inc.,December 2014; https://www.iso-ne.com/static-assets/documents/2014/12/2013_emissions_report_final.pdf.

(18) *2014 ISO New England Electric Generator Air Emissions Report*; ISO New England Inc.,January 2016; https://www.iso-ne.com/static-assets/documents/2016/01/2014_emissions_report.pdf.

(19) Rogers, M. M.; Wang, Y.; Wang, C.; McElmurry, S. P.; Miller, C. J. Evaluation of a Rapid LMP-Based Approach for Calculating Marginal Unit Emissions. *Appl. Energy* **2013**, *111*, 812−820.

(20) Wang, C.; Wang, Y.; Miller, C. J.; Lin, J. *Estimating Hourly Marginal Emission in Real Time for PJM Market Area Using a Machine Learning Approach*; 2016 IEEE Power and Energy Society General Meeting (PESGM), Boston, MA July 2016; pp 17−21, IEEE Xplore, 2016; http://ieeexplore.ieee.org/document/7741759/?reload=true (accessed 19 January 2017).

(21) Siler-Evans, K.; Azevedo, I. L.; Morgan, M. G. Marginal Emissions Factors for the U.S. Electricity System. *Environ. Sci. Technol.* **2012**, *46*, 4742−4748.

(22) Holland, S. P.; Mansur, E. T. Is Real-Time Pricing Green?: the Environmental Impacts of Electricity Demand Variance. *Rev. Econ. Stat* **2008**, *90* (3), 550−561.

(23) Jansen, K. H.; Brown, T. M.; Samuelsen, G. S. Emissions Impacts of Plug-in Hybrid Electric Vehicle Deployment on the U.S. Western Grid. *J. Power Sources* **2010**, *195* (16), 5409−5416.

(24) Graff Zivin, J. S.; Kotchen, M. J.; Mansur, E. T. Spatial and Temporal Heterogeneity of Marginal Emissions: Implications for Electric Cars and Other Electricity-Shifting Policies. *J. Econ. Behav. Organ.* **2014**, *107*, 248−268.

(25) Li, M.; Smith, T. M.; Yang, Y.; Wilson, E. J. Marginal Emissions Factors Considering Renewables: A Case Study of the U.S. Midcontinent Independent System Operator (MISO) System. *Environ. Sci. Technol.* **2017**, *51*, 11215−11223.

(26) Siler-Evans, K.; Azevedo, I. L.; Morgan, M. G.; Apt, J. Regional variations in the health, environmental, and climate benefits from wind and solar generation. *Proc. Natl. Acad. Sci. U. S. A.* **2013**, *110*, 11768−11773.

(27) Vaishnav, P.; Horner, N.; Azevedo, I. L. Was It Worthwhile? Where Have the Benefits of Rooftop Solar Photovoltaic Generation Exceed the Cost? *Environ. Res. Lett.* **2017**, *12* (094015), 1−13.

(28) Min, J.; Azevedo, I. L.; Hakkarainen, P. Net Carbon Emissions Savings and Energy Reductions from Lighting Energy Efficiency Measures when Accounting for Changes in Heating and Cooling Demands: A Regional Comparison. *Appl. Energy* **2015**, *141*, 12−18.

(29) Gilbraith, N.; Azevedo, I. L.; Jaramillo, P. Regional Energy and GHG Savings from Building Codes Across the United States. *Environ. Sci. Technol.* **2014**, *48*, 14121−14130.

(30) Hittinger, E.; Azevedo, I. L. Bulk Energy Storage Increases US Electricity System Emissions. *Environ. Sci. Technol.* **2015**, *49*, 3203−3210.

(31) Tamayao, M.; Michalek, J.; Hendrickson, C. Azevedo I.L. Regional Variability and Uncertainty of Electric Vehicle Life Cycle CO_2 Emissions Across the United States. *Environ. Sci. Technol.* **2015**, *49*, 8844−8855.

(32) Yuksel, T.; Tamayao, M.-A.; Hendrickson, C.; Azevedo, I. L.; Michalek, J. Effect of Regional Grid Mix, Driving Patterns and Climate on the Comparative Carbon Footprint of Gasoline and Plug-In Electric Vehicles in the United States. *Environ. Res. Lett.* **2016**, *11* (044007), 11.

(33) Gingerich, D.; Sun, X.; Behrer, P.; Azevedo, I. L.; Mauter, M. Air Emissions Implications of Expanded Wastewater Treatment at Coal-Fired Generators. *Proc. Natl. Acad. Sci. U.S.A.* 2017, 10.1073/pnas.1524396114.

(34) Hawkes, A. Estimating Marginal CO_2 Emissions Rates for National Electricity Systems. *Energy Policy* **2010**, *38*, 5977−5987.

(35) Hawkes, A. D. Long-Run Marginal CO_2 Emissions Factors in National Electricity Systems. *Appl. Energy* **2014**, *125*, 197−205.

(36) *Air Markets Program Data*; U.S. Environmental Protection Agency: Washington, DC, 2016. https://ampd.epa.gov/ampd/ (accessed 19 January 2017).

(37) *Market Reports*; Midcontinent Independent System Operator, Inc.: Carmel, IN, 2017; https://www.misoenergy.org/Library/MarketReports/Pages/MarketReports.aspx (assessed 1.19.2017).

(38) Wiser, R.; Bolinger, M.. *2015 Wind Technologies Market Report; LBNL-1005951*; Lawrence Berkeley National Laboratory: Berkeley, CA, August 2016; https://emp.lbl.gov/publications/2015-wind-technologies-market-report.

(39) Stafford, B. A.; Wilson, E. J. Winds of Change in Energy Systems: Policy Implementation, Technology Deployment, and Regional Transmission Organizations. *Energy Res. Soc. Sci.* **2016**, *21*, 222−236.

(40) *Wind Integration*; Midcontinent Independent System Operator, Inc., Carmel, IN, 2017; https://www.misoenergy.org/WhatWeDo/StrategicInitiatives/Pages/WindIntegration.aspx (accessed 15 September 2017).

(41) Ela, E.; Gevorgian, V.; Fleming, P.; Zhang, Y. C.; Singh, M.; Muljadi, E.; Scholbrook, A.; Aho, J.; Buckspan, A.; Pao, L.; Singhvi, V.; Tuohy, A.; Pourbeik, P.; Brooks, D.; Bhatt, N. *Active Power Controls from Wind Power: Bridging the Gaps; NREL/TP-5D00−60574*; National Renewable Energy Laboratory (NREL), Golden, CO, January 2014; https://www.nrel.gov/docs/fy14osti/60574.pdf.

(42) Kim, J. D.; Rahimi, M. Future Energy Loads for a Large-Scale Adoption of Electric Vehicles in the City of Los Angeles: Impacts on greenhouse gas (GHG) emissions. *Energy Policy* **2014**, *73*, 620−630.

(43) Marriot, J.; Matthews, H. S. Environmental Effects of Interstate Power Trading on Electricity Consumption Mixes. *Environ. Sci. Technol.* **2005**, *39*, 8584−8590.

(44) Weber, C. L.; Jaramillo, P.; Marriot, J.; Samaras, C. Life Cycle Assessment and Grid Electricity: What Do We Know and What Can We Know? *Environ. Sci. Technol.* **2010**, *44*, 1895−1901.

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