Improved Emission Functions for Generators, and How They Help Resolve a Controversy about the Emission Effects of Wind Power

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Abstract— We demonstrate a method for empirically estimating emission and fuel use functions for most of the fuel-burning electric generation units in the United States, and use it to address a controversy about the emission effects of wind power. Emission functions are necessary for estimating emissions and fuel use when measurements are not available such as in power system simulation scenarios, unit commitment and dispatch decisions, and when measurement equipment is absent, turned off, or malfunctioning. Commonly, the "functions" used assume that emissions of a generation unit are simply a constant multiple of its output. Our functions include the impacts of ramping and startup on emissions. Because wind power increases the frequency of start-ups and ramping by fuel-burning generators, some have claimed that wind power actually increases emissions. We calculate emission functions for all of the combustion-based generators in the Texas grid, and apply them to the output of high and low wind power penetration scenarios to carefully estimate the emission impacts of increased wind power penetration.

I. Overview

With the continued integration of wind power into the power system there is the potential for more variability in generation output from fuel-burning generators because of the variability of wind. Variability in fossil-fueled generation means an increase in the instances and magnitude of ramping ~~from one~~ generators from one set point to another. During times of ramping up, the change in heat input required to move a generator from one level of generation output to another will likely change the emissions rate of the unit. The average effect of ramping on emissions is positive if holding a unit's monthly electric energy output constant but increasing its ramping increases its emissions. If the average effect of ramping on emissions, averaged across the generation units in a region, is positive, this will partially offset the emissions reductions that wind power offers. If it does, then estimates of the effect of ramping on emissions, for each generation unit, will enable system operators to make better economic dispatch decisions both in general and in response to the variability of wind.

We accurately model hourly emission rates of generators, as a non-linear function of current-hour MWh output, recent ramping, and how long ago the unit started up. Specifically, we estimate NO_x and~~,~~ SO_2

emission functions, with plans to estimate similar functions for CO_2 emissions, for all of the fuel-burning generators supplying the grid in Texas and New York.

Wind power may increase emissions because it increases instances of ramping, startups, and partial-load operation of fuel-fired generation. Our functions, which incorporate these impacts, can be used in comparing -scenarios that differ significantly with respect to ramping or start-ups, such as a high-wind-penetration scenario and a low-wind-penetration scenario. We apply our estimated functions to simulation data of two scenarios differing in wind penetration from the Electric Reliability Council of Texas (ERCOT) in order to analyze the emission effects of wind power. In the near future we will expand this to five scenarios from ERCOT and two scenarios from the New York Independent System Operator (NYISO).

II. Literature Review

Some research has been done exploring the relationship between ramping fossil fuel-burning units and the resulting impacts on emissions. Simulations have shown that 20 to 30 percent renewables penetration in WECC would result in a significant increase in ramping of generation units, including those fueled by coal (GE Energy, 2010). Analysis of power spectrum density plots of wind variability has found that the relatively large amplitude of low frequency fluctuations of wind output (in the range of hours), compared to high frequency fluctuations (minutes or seconds), highlights the importance of using slow ramping generation, such as coal or natural gas fired units, to back up variable wind generation (Apt, Fertig, & Katzenstein, 2012). Increased instances of ramping or increases in the magnitude of ramping could increase emissions above the rate at which they occur when at a steady state of constant generation. Increasing instances of rampingThese higher emission rates could then increase overall emissions, potentially offsetting gains from wind power.

The use of fossil fuel operating reserves to back up wind has been shown to offset at least some of the gains in emissions reductions from wind and solar power (Katzenstein & Apt, 2009) (Fripp, 2011). Apt and Katzenstein (2009) use regression analysis to model emissions of NO_x and CO_2 for two types of fast-ramping natural gas generators and apply the results to a small 2 gas, 1 wind, 1 solar unit system. To find expected reductions of emissions they assume emissions are reduced linearly according to the penetration of wind power. Insight can be drawn from a simple example they give. They assume a system with two tons of CO_2 emissions per MWh as a baseline. Then with 10 percent wind penetration expected emissions reductions would be 0.2 tons per MWh with total system emissions of 1.8 tons per MWh. If actual emissions were different, for example 1.9 tons per MWh, then there is an increase from expected reductions by 0.1 tons per MWh. Their results show 75-80% reductions in CO_2 emissions from what would be expected if the ramping of the units caused no additional emissions. For NO_x, depending on emissions controls emissions reductions range from 30-50% of expected reductions to an increase of 2-4 times the expected reductions. Fripp [3] also uses gas operating reserves and finds that 6% of the emissions that would come from wind power are mitigated by the operation of reserve power. This comes from inefficiency in the system which runs excess combined cycle (CC) and combustion turbine (CT) generators, and uses CT generators because they can start quickly instead of more efficient options.

Estimates of the effects of wind energy on coal unit ramping and emissions have been similarly disparate. Bentek energy released a report in April 2010 saying that wind energy causes increases in SO_2 and NO_x emissions in both PSCO (Colorado) and ERCOT (Texas) and increases in CO_2 emissions in PSCO (Bentek Energy, LLC, 2010). Colorado's Xcel energy later refuted this report saying that their large additions in wind energy have resulted in an overall decline in emissions (Prager, 2010). Finally, a study by Lew et al. found insignificant impacts on emissions from ramping but significant impacts on emissions from partial load operation and from starting up, for both coal and gas plants (Lew, et al.).

III. Emission Functions Methodology

Data for estimating emission functions is taken from 2010 U.S. Environmental Protection Agency (EPA) Continuous Emissions Monitoring Systems (CEMs) data. Data is reported hourly for each generator for the entire year. Variables used in the study are found in Table I. Carbon dioxide (CO_2) emissions are proportional to heat input, so we refer interchangeably to estimating heat input and estimating CO_2 emissions. Additional data is taken from the U.S. Energy Information Administration (EIA) Annual Electric Generator Report (EIA-860) to physically locate generators and determine nameplate capacity levels.

Ordinary least squares (OLS) estimates of time series data often exhibit strong serial correlation in their errors, meaning that current errors are correlated with past errors. This violates the standard assumptions of OLS regression, resulting in standard errors that are biased and estimates which are no longer efficient. There are two solutions to this problem. The standard errors can be corrected or additional information can be utilized from the dynamics of the serial correlation to improve forecasts. These dynamics in time series data are used by us to help forecast emissions from each generator in the U.S. using ARMAX models. ARMAX allows for forecasts to include underlying data generating processes from autoregressive (AR) and moving average (MA) components in addition to the use of exogenous explanatory variables (denoted by the "X" in ARMAX). These variables consist of the level of generator output, any increases in output (ramping up), any decreases in output (ramping down), and whether the unit has started up in the past few hours. Therefore the final estimated emission equations have the following form for generator *i* and emission type *e* (NO_x or SO_2):

$$E_{iet} = \mu + \sum_{n=1}^{p} \phi_n E_{ie(t-n)} + \theta_1 \epsilon_t + \sum_{m=1}^{q} \theta_{m+1} \epsilon_{t-m} + \alpha_1 GLOAD_{it} + \alpha_2 (GLOAD_{it})^2 + \sum_{k=0}^{u} \beta_k Upramp_{i(t-k)} + \sum_{j=0}^{r} \lambda_j Downramp_{i(t-j)} + \sum_{h=0}^{s} \gamma_h Startup_{i(t-h)} \qquad (1)$$

where p and q are the AR and MA lag lengths, and u, r, and s are the lag lengths to be included for the ramping variables and startup dummies.

Table I.
VARIABLE DESCRIPTIONS.

Variable Name	Description	Measure
GLOAD	Gross Generator Output	MWh
NOXMASS	Nitrogen Oxide Emissions	lb/hour
SO2MASS	Sulfur Dioxide Emissions	lb/hour
UPRAMP	$\begin{cases} GLOAD_t - GLOAD_{t-1}\ if \geq 0 \\ Else\ 0 \end{cases}$	MWh
DOWNRAMP	$\begin{cases} GLOAD_t - GLOAD_{t-1}\ if \leq\ 0 \\ Else\ 0 \end{cases}$	MWh
STARTUP	1 if generator has started up in the last hour. 0 otherwise.	Dummy Variable

We estimate functions using equation (1) for 244 generators in Texas. To estimate functions by hand for every generator would be time consuming. Therefore an automated procedure has been coded to estimate the functions for each generator. This process involves first determining the ARMA structure for each emission type. This is done by estimating an ARMA regression of up to three AR and three MA lags, and choosing the best fitting model using Akaike Information Criterion (AIC) (Akaike, 1974) and Bayesian Information Criterion (BIC) (Schwarz, 1978). For the results presented here, functions are estimated with one lag of both the AR and MA component due to problems estimating functions with higher order lags for some generators.

We then group generators into two fuel types, natural gas or coal. We estimate functions for each type of emission for all generators within the particular fuel type using a large number of lags for the ramping and startup variables. The significance of certain lags is counted for each fuel type and is used at the end to choose a representative function for all generators of that type. This representative function is chosen by choosing a number of significant lags that most generators share. For example, functions of NO_x emissions of natural gas generators are chosen that have four ramping lags as most generators did not have significant ramping impacts past the fourth lag. This results in parsimonious functions for each fuel type and emission type with unit specific coefficients. These functions have been estimated for all fuel emitting generators in Texas but could be estimated for generator that reports hourly generation output to the EPA or other agency.

IV. SIMULATION DATA

ERCOT simulated hourly operation of their system for one year using PROMOD software. PROMOD is an electric market simulation software which runs unit commitment and economic dispatch, with transmission grid topology and constraints, and with ramping constraints for units. Two simulations were run using two different wind penetration scenarios. The first “low” wind penetration scenario is based on the current generation makeup of Texas which consists of about 10,000 MW of wind capacity. The “high” wind penetration scenario adds 6,500 MW of wind capacity for a total of about 16,500 MW in capacity. Both scenarios are run with 2012 load conditions, and the projected 2016 transmission system which has wind-oriented expansions. The reason for using the 2016 transmission system is that under the high wind penetration scenario, the current system must curtail or spill wind to stay within transmmission constraints.

To estimate emissions from the two scenarios, the generators from the ERCOT data are matched with generators from the EPA and EIA data sets using generator characteristics such as unit name, fuel type, latitude, longitude, and capacity. The estimated emission functions are then applied to each generator's simulated hourly output under each scenario to produce hourly estimated emissions. For natural gas generation, SO_2 emissions are ignored due to their low magnitude and errors in the EPA data.

V. RESULTS

After applying emission functions we sum emissions of SO_2 and NO_x over the year for- generators of each fuel type and do similar analyses for our other interesting variables, generation output, ramping incidents, startup incidents, and the magnitudes of the ramping incidents. Simulation results for coal generation are in Table II and analysis is provided afterwards.

TABLE II.
COAL SIMULATION RESULTS

	Low Wind Penetration	High Wind Penetration	Percent Change
Coal Generation	127,773,413 MWh	123,714,479 MWh	-3.2%
Coal Startups/GWh from coal	0.00325	0.00340	4.4%
Coal Ramp Incidents/GWh from coal	0.154	0.284	84.4%
Average Coal Ramp	125.71 MW/hr	94.4 MW/hr	-24.9%
Standard Deviation of Coal Ramps	88.65 MW	70.99 MW	-19.9%

The simulation results of coal output provide some interesting information on what happens to coal generation in Texas under the higher wind penetration scenaio. Total generation decreases but the actual ramping and startup occurences increase by a lot. Despite this the magnitude of the ramps actually decreases. This may be caused by ramping due to wind variability being of a smaller magnitude than ramping due to other reasons such as load following, unit problems, or grid constraints. The impacts on emissions from this change in coal unit operation are not easily predictable. According to previous work these increases in ramping incidents may increase emissions, but at the same time the ramping incidents are smaller, and the total generation output is smaller. Results from the emission analysis are found in Table III.

TABLE III.
COAL EMISSIONS ANALYSIS RESULTS

	Low Wind Penetration	High Wind Penetration	Percent Change
Coal NO_x Emissions	157,003,520 lbs	151,001,544 lbs	-4.0%
Coal SO_2 Emissions	655,989,596 lbs	632,268,091 lbs	-3.6%

Despite the 3.2% decrease in coal generation from the low to high wind penetration scenario over the year, both NO_x and SO_2 emissions decrease by more than this. In addition this decrease in emissions occurs despite the increase in startups and ramping. Natural gas results show a similar story and can be found in Table IV with analysis following.

TABLE IV.
NATURAL GAS RESULTS

	Low Wind Penetration	High Wind Penetration	Percent Change
Gas Generation	115,223,385 MWh	93,657,898 MWh	-18.7%
Gas Startups/GWh from gas	0.101	0.114	13%
Gas Ramp Incidents/GWh from gas	0.86	0.95	10.5%
Average Gas Ramp	78.32 MW/hr	78.77 MW/hr	1.01%
Standard Deviation of Gas Ramps	31.3 MW	31.1 MW	-0.64%
Gas NO_x Emissions	438,962,830 lbs	268,648,138	-38.8%

The simulation results for natural gas show large changes in natural gas fired unit operation from the increase in wind penetration. Megawatt output drops by 18% but ramping incidents per per gigawatt hour increase by 9%. This reflects the increased variability on the system from higher wind penetration as gas must ramp up and down more often in order to fill in for gaps in variable wind generation. In the low wind scenario, gas was still filling in somewhat for wind variation, but coal was not. In the high wind scenario there is so much wind on the system that it often ends up replacing coal as well. This is a reason for the larger percentage increase in coal ramps per GWh compared to natural gas ramps per GWh.

NO_x emissions from natural gas units, percentage wise, increase by more than twice the decrease in MW generation. This occurs despite the moderate increase in ramping incidents and increase in average ramping magnitude.

Finally, Table V shows total results for all units combined which includes, in addition to coal and natural gas, a few highly polluting petroleum coke fired units.

TABLE V.
TOTAL RESULTS

	Low Wind Penetration	High Wind Penetration	Percent Change
Wind Generation	35,430,595 MW	63,214,866 MW	78.42%
Fuel-Fired Generation	285,488,976 MW	259,854,011 MW	-8.98%
Total SO_2 Emissions	665,204,116 lbs	641,394,291 lbs	-3.6%
Total NO_x Emissions	596,694,675 lbs	420,389,134	-29.5%

The total emission results offer further information on the impact of wind penetration on emissions. It can be seen that the 63% increase in wind capacity results in a 78% increase in total wind generation. Total fuel-fired generation decreases by 9% with the resulting emission impacts of a decrease in SO_2 emissions by 3.6% and decrease in NO_x emissions by 29.5%. The reason for the disproportionate change in SbO_2 emissions compared to NO_x emissions is that wind generation displaces natural gas generation which emits a negligible amount of SO_2. NO_x emissions decrease by more than the decrease in fuel-fired generation.

It becomes apparent why emissions decrease more than generation if the type of generation that wind replaces is considered. Wind can disproportionately displace generation that is at the top of the bid stack. This generation is expensive and highly emitting due to being less fuel efficient. In addition, previous studies have found that partial-load operation can decrease emission rates per MWh for steam units [6].

VI. Conclusions

We show a method to estimate accurate emission functions for fuel-fired generation and apply these functions to two simulated scenarios in Texas. One scenario is considered a “low” wind penetration scenario and the other a “high” wind penetration scenario. With our estimated emission functions we show results indicating that the impact of wind generation on emissions is not as the literature suggests. Emissions actually decrease under the high wind penetration scenario compared to the low wind penetration scenario. This occurs despite the increase in coal ramping and startup episodes which has previously been described as the root cause of emissions increases from high wind penetration. This is due to the fact that wind displaces natural gas more than it displaces coal, especially highly inefficient generators. Additionally steam units may be operating at partial load more often, where they may be more efficient.

VII. Future Work

The previous sections all discuss inputs and results that have been already produced. Work has been done to quickly expand on these inputs and results to generate a more thorough and comprehensive picture of the impact of wind penetration on emissions. The following steps have been made to allow this to happen. The EPA CEMs SO_2 emissions data has been fixed so that estimates for SO_2 emission functions for gas generators are valid. Emission functions for heat input (mmBtu/hr) have been generated which can be easily converted into CO_2 emissions (linear conversion factor). Finally all emission functions will be estimated with up to three lags of AR and/or MA terms instead of the 1 term of each we used for current results.

There are results upcoming of three additional scenarios from ERCOT which will have 4,000, 23,000, and 29,500 MW of wind capacity. Additionally there will be results of two scenarios from the NYISO with 1,275 and 6,000 MW of wind capacity. The additional ERCOT scenarios will allow us to better characterize how emissions change over a larger span of wind capacity on the system. This can help answer the question, do emissions change linearly as wind penetration increases? The two scenarios from the NYISO will allow comparisons between two systems with different mixes of generation. ERCOT has almost 50% of its generation capacity in coal while the NYISO is dominated by nuclear and hydropower with lesser amounts of gas and coal. These additional scenarios, improved emission functions, and comparisons between systems will allow us to draw further conclusions regarding the impact of increasing wind penetration on NO_x, SO_2, and CO_2 emissions.

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