Assessing the Emission Benefits of Renewable Energy and Energy Efficiency using EPA's AVoided Emissions and geneRation Tool (AVERT)

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ABSTRACT

Despite an increase in stack controls on electric generating units (EGU), states continue to seek innovative ways to meet air quality standards as EPA tightens the National Ambient Air Quality Standards (NAAQS) to protect public health and the environment. EPA acknowledged that energy efficiency and renewable energy (EE/RE) policies and resources are eligible emission reduction measures for Clean Air Act plans in the 2012 Roadmap for Incorporating EE/RE Policies and Programs in State Implementation Plans. In addition, the proposed Clean Power Plan utilizes EE/RE to demonstrate the best system of emission reductions for electric power sector CO_2 emission rate reductions.

This paper presents a novel approach, embodied in EPA's AVoided Emissions and geneRation Tool (AVERT), to assist state and local air quality managers and stakeholders in estimating avoided CO_2, NOx and SO_2 emissions from EGUs due to the implementation of EE/RE policies and resources. AVERT employs a statistical algorithm, using the behavioral characteristics of individual EGUs from publicly available hourly historical generation and emissions data. AVERT circumvents several common assumptions inherent in simplified avoided emissions methods. The tool is publicly available.

We review related existing approaches for analyzing avoided emissions, review the AVERT methodology and its validation, and demonstrate the tool's capabilities through a short case study. The case study suggests that, across all ten AVERT regions, wind and baseload EE resources are more effective than solar or a representative portfolio of EE resources at reducing emissions of CO_2. NOx is reduced with approximately the same efficacy by all four temporal profiles of EE/RE resources. We show that avoided CO_2 and NOx emissions are sensitive to the composition of the underlying fossil fuel fleet within an AVERT region.

1. INTRODUCTION

Over the last two decades, emissions of major criteria air pollutants (particularly SO_2 and NO_x) from electric generation units (EGUs) in the United States have declined markedly.[1] From 2005 to 2012, the number of coal-fired EGUs reporting to the U.S. Environmental Protection Agency (EPA) operational flue gas desulfurization technology (FGD) nearly doubled from 23% to 44%, representing a 100-percent increase in the amount of coal generation covered by an FGD (from 32% to 66%).[2] Similarly, the number of coal units reporting an operational selective catalytic reduction (SCR) system increased by half during that time period, from 21%-34% (representing 33% and 47% of coal generation, respectively). The installation of these technologies has resulted in significant local and regional air pollutant emissions reductions across the U.S. generating fleet. EPA has continued to protect public health by revising NAAQS based on current science, and states have sought innovative emission reduction measures to attain updated standards. At the same time, states and local agencies have recognized increasing investments in EE/RE, and have expressed interest in accounting for the emission benefits of these investments. In response to this interest, EPA released the Roadmap for Incorporating Energy Efficiency and Renewable Energy in State Implementation Plans in July 2012. This document provided clarifying guidance for states on incorporating (EE/RE) into ozone and particulate matter (PM) State Implementation Plans (SIPs).[3]

Energy efficiency and renewable energy have the potential to reduce multiple pollutants by avoiding generation from fossil resources, and because many of these resources are cost effective even without emissions benefits, they pose an important opportunity to states, tribes, and territories to meet multiple clean air standards through low-cost, transformative technologies. However, emissions reductions from EE/RE are “indirect” and difficult to characterize. The temporal and spatial variation inherent in different EE/RE resource options (e.g., demand reduction at different, non-uniform times of day; the unpredictability of physical meteorological effects), and the complexity with which EE/RE resources interact with the underlying electricity systems (e.g., existing supply resource base, market characteristics) makes quantifying avoided emissions challenging. Determining from which EGUs production is avoided, and thus which emissions are reduced and where, is neither intuitive nor obvious.

To address this difficulty, a number of methods have been proposed and variously used. The simplest methods tend to make implicit assumptions that may incorrectly characterize a system; the most complex methods are often inaccessible to regulators. This paper presents a novel modeling tool, the Avoided Emissions and geneRation Tool (AVERT), to assist state and local air quality managers, the U.S. Environmental Protection Agency (EPA), and other interested stakeholders in estimating the NO_x, SO_2, and CO_2 emission impacts of EE/RE resources from stationary electric generating units (EGUs). AVERT is a statistical tool, deriving behavioral characteristics of different generating units from hourly historical generation and emissions data collected and made publicly available by EPA.

The sections that follow provide a discussion of related literature and the key limitations of existing approaches for studying avoided emissions; an overview of the AVERT methodology, its contribution to the literature, and its validation; a demonstration of the tool through a short case study; and a concluding discussion about next steps and future research opportunities.

2. BACKGROUND

Quantifying and characterizing avoided emissions from EE/RE resources has been an active area of research over the past decade. When new EE/RE is brought online, it avoids the need to dispatch existing EGU or, over the long-run, build new incremental generation to serve load. The generation which is not dispatched because of EE/RE is the avoided generation, and the consequently reduced emissions are termed the "avoided" emissions. Over the short run, new EE/RE resources avoid generation and emissions from existing EGU. However, determining from which EGUs generation is avoided, and when, is notoriously difficult to quantify.

In most circumstances, generation from EGUs is avoided on the basis of variable cost and availability, which in turn is dictated by operational and transmission constraints. However, without *a priori* knowledge of costs and constraints, we cannot specify from which EGUs generation is avoided. Even with such information, the interaction between each EGU in a system is complex; models are required to determine how multiple EGUs should be economically dispatched. In electric system dispatch, increasingly expensive EGUs are brought online as load (demand) increases. At any given time, the last EGU to be brought online is termed the "marginal" EGU. Across an area there may be multiple EGUs that are marginal, or near marginal, at any given moment, and this cohort of EGU may change significantly from hour to hour.

The difficulty in determining how EE/RE impacts an electrical system, and thus avoids emissions, is demonstrated by a simple example (see Figure 1). In this illustration, a 1,000 MW system is served by six EGU, two of which are coal-fired and four of which are natural gas-fired. In the ideal circumstance, units are dispatched in economic merit order, with lower variable cost (but higher emissions rate) coal dispatched first and higher cost (and lower emissions rate) gas dispatched after. The imposition of a new 200 MW solar program avoids generation almost exclusively from gas resources (CO_2 rate 0.5t/MWh) and little coal (CO_2 rate 1.0 t/MWh), having an avoided emissions rate of 0.52t/MWh. In this example, a larger 600 MW solar program avoids coal unit generation as well, leading to a higher avoided emissions rate of 0.59t/MWh. This size dependency cannot be captured without knowledge of the system's dispatch dynamics.

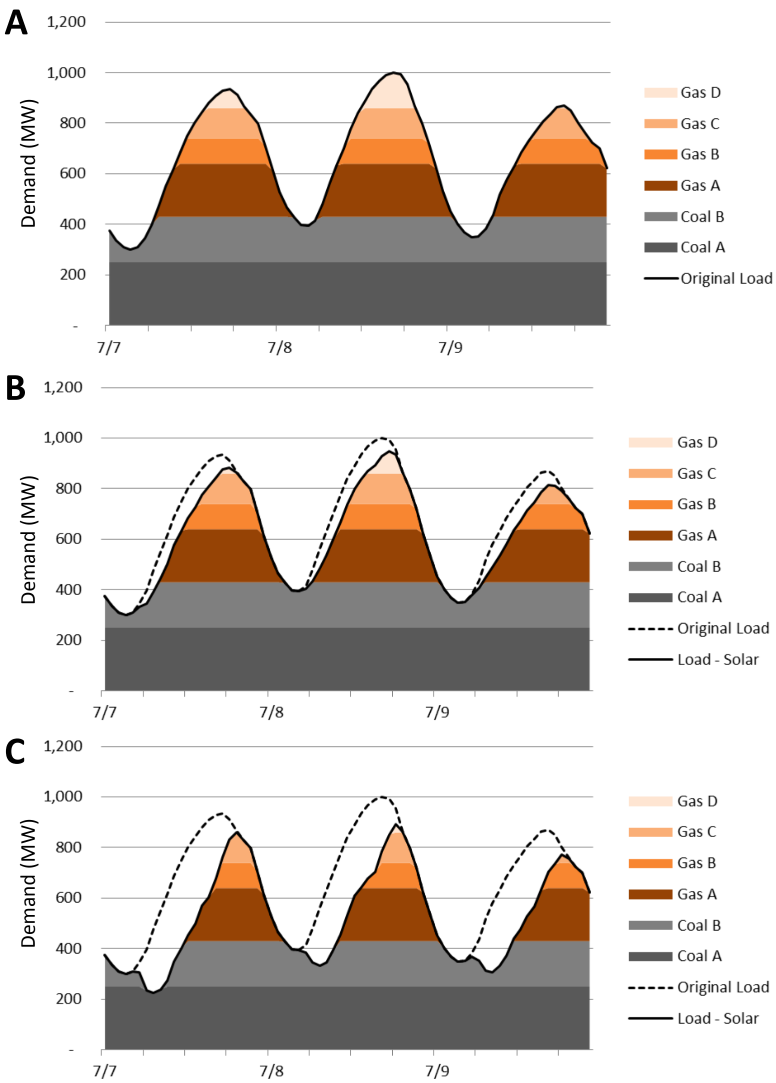

Figure 1. Simplified example of system dispatch over a three day period, and avoided generation from a solar program. (A) Base case; (B) 200 MW solar; (C) 600 MW solar.

The example here is highly simplified: in reality, units are dispatched with consideration to their ramp rate, transmission constraints, and ability to cycle. So wherein the simple case the smaller Coal B unit is simply shut off for two hours, accommodating the unit's limited ramp rate might require that Coal A also ramp down, allowing Coal B to maintain a limited level of generation. Or Coal B might decommit (i.e. shut down completely) for a full outage cycle, returning online the next day, if it were economic to do so. Similarly, the reduction during the peak hour might avoid generation at both the highest cost resource and some of the next highest cost resource – or it might avoid generation at a fraction of several high cost resources, or even allow several otherwise low-cost resources to ramp down slightly from an overclocked level of output to a more sustainable level. In many cases there are effectively multiple simultaneous marginal EGUs. Load increases or reductions may thus impact multiple EGUs simultaneously all subject to differential costs, operating constraints, and transmission limitations. Backing out these constraints to estimate how EGUs, and thus emissions, respond to EE/RE is difficult.

A number of methods have been proposed (and used) to estimate how emissions are reduced from EE/RE. The most common methods fall into one of two general categories—statistical methods based on historical data, or numerical electricity dispatch models. There are inherent tradeoffs and differences between the two categories. Statistical methods, spanning the gamut from simple calculations to detailed data deconstructions, are grounded in historical data and may be accessible, but can be limited and subject to implicit and untested assumptions. Numerical dispatch models can represent systemic changes in the power system well, but can often be burdensome with respect to data requirements, and are limited in reality about market structure and other constraints. Within these categories, models differ with respect to the level of detail, the exogenous and/or implicit assumptions they rest upon, and the level of accessibility for decision-makers and other key stakeholders.

A widely used "statistical" approach for estimating avoided emissions is to simply calculate an average emissions rate of all operating EGUs in a region. By including all units this method may significantly underestimate real emissions reductions where there are numerous non-emitting (and non-marginal) EGUs such as nuclear, hydroelectric, and renewable resources, or overestimate avoided emissions in regions with significant coal capacity.* As a refinement, some methods distinguish between EGUs that maintain baseload operations and those that directly respond to changes in demand, and provide the emissions rate of this subset of generating units as an avoided emissions rate.† These methods make significant assumptions about the relative weight of those units in the analysis, and rely on broad assumptions about how units operate.[4,5,6,7,8, 9]

Some statistical methods exploit more detailed historical data to estimate avoided emissions. At the simplest level, a "slope factor" simply assumes that the slope of a best-fit line between generation and emissions in a region represents a regional marginal emissions rate.‡ This mechanism is highly aggregated and takes into account neither temporal patterns nor specific EGUs.[10,11, 12] Modifications to the slope-factor method have been proposed and used, including reviewing the slope hourly changes in generation and binning to account for total generation levels,[13] and using reduced form models to define avoided emissions by level for wind generation, implicitly accounting for fossil output. While these methods seek to identify a cohort of units that were likely on or near the margin (and thus determine an avoided emissions rate), they tend to rely on a set of exogenous assumptions about how close to the margin different units reside and have difficulty examining more geographically detailed avoided generation. In a paper designed to examine the impact of renewable energy on avoided health impacts, Siler-Evans et al. (2013) refined the slope factor method to examine hourly incremental changes in emissions against incremental changes in energy, and divided the year into bins of total generation to account for fundamentally different dispatch at different load levels.[13] While this method captures discrete emissions changes at different load levels and allows for temporal differentiation, the results are aggregated on a regional basis.

The second category of methods used to calculate avoided emissions from EE/RE resources employ, directly or indirectly, numerical dispatch models. In 2002, researchers from the EPA proposed the Average Displaced Emissions Rate (ADER) model.[14] The ADER model generalized the results of specific runs conducted in the Integrated Planning Model (IPM), where each run represented a different EE/RE load shape; the ADER model characterized how blocks of units responded to imposed changes in generation. This method, based on the output of a simulation model, may have circumvented concerns from using historical data, but relied on a coarse-resolution model with non-chronological dispatch. Zhai et al.[15] studied the potential for avoided emissions from solar PV in the US using the EnergyPLAN

* Our simplified example in Figure 1 has an average emissions rate of 0.82t/MWh.

† The "load following" emissions rate of the responsive gas units in our simplified system is 0.50t/MWh (assuming only the gas units are "responsive").

‡ The slope factor of our simplified illustrative system is 0.55t/MWh.

model, a medium-resolution electricity dispatch optimization model representing technologies in groups. A goal of the research was to use a simple, low-input requirement model, but this traded off the ability to represent critical unit-level decisions such as unit-commitment. Denny and O'Malley used a similar approach using a dispatch optimization model without unit commitment to study avoided emissions potentials for wind power in Texas.[16]

Other researchers have used finer-resolution production cost models with hourly chronological dispatch and unit-commitment to evaluate EE/RE avoided emissions. Denholm, Margolis and Milford (2009) employ ABB's PROSYM production cost model to evaluate how deep penetrations of solar energy (up to 10%) in western US states could avoid generation and emissions throughout the west.[17] Fisher et al. (2011) also used the PROSYM engine to test how a series of EE/RE projects in California could impact individual generators across the Western U.S., specifically examining emissions reductions in California air districts. Fisher et al. found that, depending on the location of the EE/RE resource, avoided emissions could either be highly localized or based on generators across state lines.[18] Coal generators were also impacted more than might be expected based on traditional indicators of marginal units. As a third example, Valentino et al. (2012) constructs an optimization model with unit-commitment and electricity dispatch to estimate emission reductions from increased wind power in Illinois.[19]

AVERT, presented here, captures some of the same statistical elements as Siler-Evans, but makes important methodological departures to capture the behavior of individual fossil generators. The basis of AVERT extends the work of James and Fisher (2008),[20] who proposed a Load-Based Probabilistic Emissions Model (LBPEM), a mechanism of deriving statistics from historical behavior of individual fossil generators. LBPEM and AVERT predict future behavior from statistical relationships between individual generators. When overlaid with a temporal EE/RE profile, these models then calculate generation and emissions differences on an hourly basis. Overall, while these methods are not without their limitations—they are unable to capture transmission constraints or predict changes in behavior in systems that have undergone systemic change—the tool presented here aims to be public data driven, transparent, and highly accessible.

3. METHODOLOGY

The AVERT Model

AVERT belongs to the statistical class of models that predict behavioral changes. Unlike traditional engineering cost-based electricity system dispatch and unit-commitment optimization models, AVERT does not use operating costs to estimate how and when a unit should be dispatched to meet load requirements. Rather, the model predicts unit operation based on historical patterns and use. Two significant advantages of this approach are that (a) the model is driven entirely by historical, publicly available data (the actual generation output and emissions of real units in the recent past), and (b) the model makes few, if any, explicit or implicit assumptions about unit behavior, fuel, operations, or requirements.

Using a historical dataset of hourly emissions and generation, the model replicates actual unit generation "behaviors" such as baseload, intermediate, and peaking operation patterns, must-run designations (i.e., requirements to operate for reliability reasons), and forced and maintenance outages. In addition, the model accurately represents the relationship between unit generation and emissions, with modeled characteristics such as a decreasing heat rate (i.e., increasing efficiency) at higher levels of output, higher emissions from units that are spinning up, and seasonally-changing emissions for units with seasonal environmental controls. All of these behaviors are derived quantitatively from historical hourly data with no user intervention. AVERT is built upon a platform that allows non-expert users to easily, quickly, and flexibly evaluate the individual unit reductions from EE/RE resources with a high degree of accuracy, and at a low cost per use. The tool is publicly available from the U.S. EPA (www.epa.gov/avert) and is provided free of charge.

AVERT is divided into two key components, a Statistical Module that provides the key calculations and estimates of electric generating unit behavior, and a Main Module, which estimates hourly avoided generation and emissions for each unit based on a user-defined hourly EE/RE profile. The effect of different types of EE resources, as well as wind and solar technologies[§] on the magnitude and location—at the county, state, and region regional level—of avoided sulfur dioxide (SO_2), nitrogen oxides (NOx), and carbon dioxide (CO_2) emissions can be evaluated. The model currently maintains historical data from 2007 through 2014, and is expected to be updated annually in the first quarter of each year.

Analyses are conducted by region, with the continental United States divided into ten reasonably autonomous electricity-market trading and dispatch areas. These AVERT regions are based on aggregations of the eGRID subregions used by EPA, and are similar, but not identical, to North American Electric Reliability Corporation regions. Figure 2 below shoes a map of the model's regions, several of which represent electricity market areas or balancing authorities. Analysis based on smaller regions, such as eGRID regions, risks missing important interdependencies between the EGUs in a larger region (e.g., the impact of New Jersey load reductions on Ohio EGUs). Using still larger regions, such as the Eastern Interconnect, spreads the influence of load reductions too widely, making it difficult to ascribe load reductions at a particular location to a reasonable cohort of EGUs.

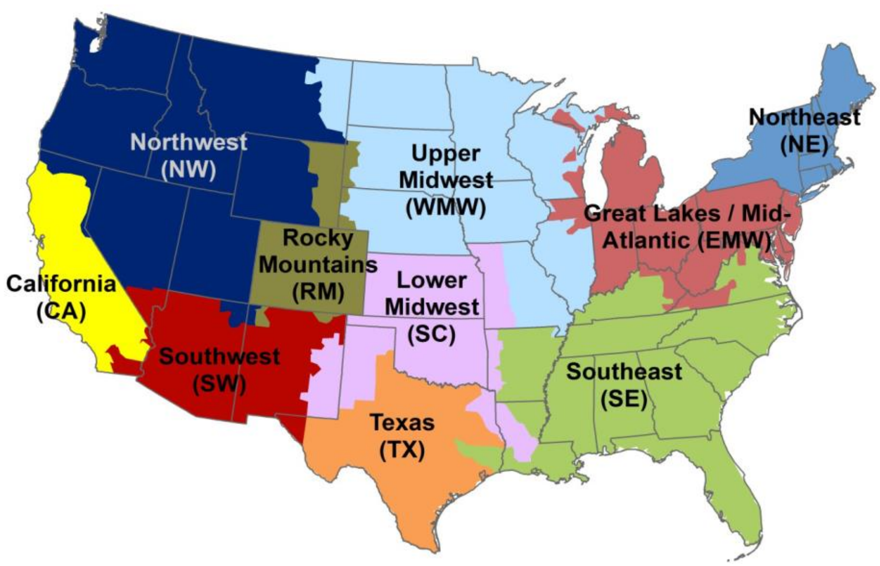

Figure 2. Map of AVERT's ten regions.

For each region, the Statistical Module provides the model's core statistical analysis. The model begins by summing up all fossil-fuel generation in each hour under analysis to arrive at a total regional fossil-

[§] AVERT has the capability of estimating emission impacts of many other renewable energy technologies.

fuel generation served (termed "fossil-fuel load") by hour. These hourly sums of fossil-fuel generation are sorted from lowest to highest generation level and grouped into forty-two (42) fossil-fuel load "bins" for the purpose of collecting statistics for each EGU at each approximate load level. Forty of the bins contain information from the same number of hours (approximately 220); the bins for the lowest and highest fossil-fuel loads contain just 20 hours each to best represent these extreme load levels. Because bins are dynamically determined such that they hold the same number of hours (rather than being set at specific load levels), the size and range of the bins vary by region and year.

AVERT's core algorithm first gathers statistics about how each EGU responds to the generation requirements of each fossil-fuel load bin. Three types of probability distributions are constructed: frequency of operation by fossil-fuel load bin, generation level by fossil-fuel load bin, and heat input and emissions by generation level. These distributions are represented in Figure 3, below.

- In the first set of probability distributions (Figure 3a), AVERT calculates the share of hours within each fossil-fuel load bin for which a particular unit is turned on (i.e., has generation greater than zero).
- The second set of probability distributions (Figure 3b) calculated by AVERT describes generation output for each EGU in operation in each fossil-fuel load bin. AVERT divides each EGU's generation into evenly-spaced "unit generation bins." For each of the fossil-fuel load bins, AVERT determines the number of hours in which the unit generated at an amount within each of the unit generation bins. In this way, the model creates a discrete probability distribution of generation for each fossil-fuel load bin during all hours in which the EGU is in operation.
- The final set of probability distributions (Figure 3c) relate EGU heat input and SO_2, NO_x, and CO_2 emissions to unit generation. For heat input and emissions, statistics for the ozone season and non-ozone seasons are gathered and stored. AVERT creates eight discrete probability distributions—ozone season SO_2, NO_x, and CO_2 emissions and heat input, and nonozone-season SO_2, NO_x, and CO_2 emissions and heat input—for each EGU at each of the unit generation bins.

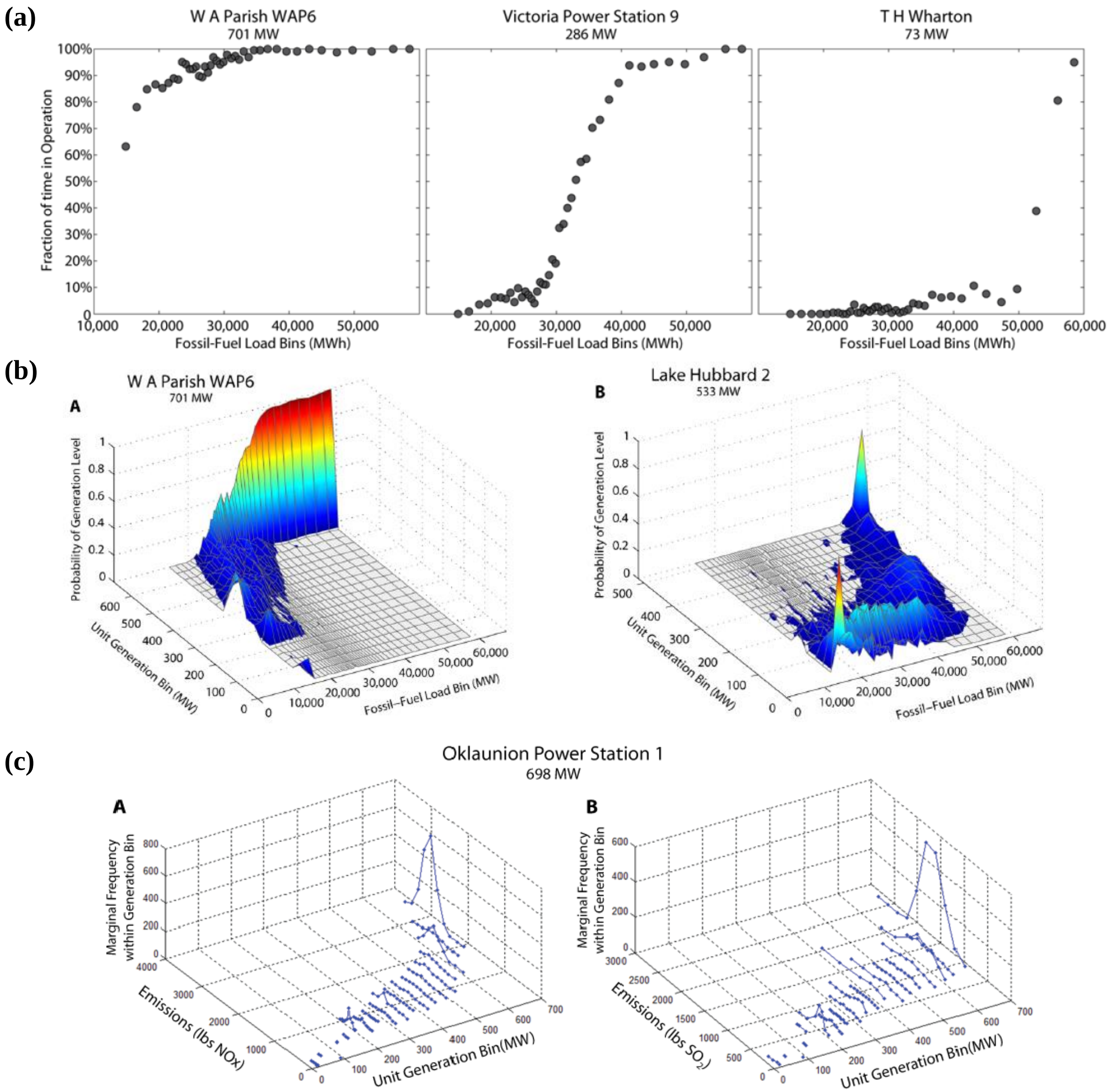

Figure 3. AVERT's statistical algorithm: (a) determine fraction of time units are online, (b) determine generation of units at different load requirements, (c) determine emissions level at generation output

After baseline statistics have been gathered, AVERT estimates how units may respond outside of the range of historical fossil-fuel load bins. The algorithm extrapolates each EGU's statistics below and above base-year regional load requirements. Two sets of probability distributions are subject to extrapolation: probability of operation and generation level for each fossil-fuel load bin.

Finally, the Statistical Module calculates the expected value of generation, heat input, and emissions for each EGU at each of the fossil-fuel load requirement bins, from zero MW up to the coincident maximum generation of all of fossil-fuel EGUs in a region. A Monte Carlo analysis uses discrete probability distributions to estimate key variables' range and expected values for each EGU in each fossil-fuel load bin.

AVERT's Main Module estimates the avoided emissions from EE/RE resources for every individual fossil-fuel EGU in a region; for general users, this information is aggregated to the county level (although users can also aggregate to state and regional levels). The Main Module uses the expected value of generation and emissions at each load level for each EGU to estimate hourly output both before and after EE/RE. Users enter or choose an EE/RE profile, and the Main Module calculates the before, after, and difference in EGU-specific generation and emissions. The differences between emissions resulting from the base year load curve after the adjustment to include the load impact profile of an EE/RE program are the "avoided emissions." Additional details about AVERT's methodology and algorithms are available in model's user manual.[21]

Data

AVERT uses Air Market Program Data (AMPD) from EPA's Clean Air Markets Division (CAMD).[22] For the purposes of tracking and verifying emissions, and monitoring emissions trading programs, AMPD collects extensive operational data from nearly all operating fossil-fuel EGUs with generating capacities greater than 25 MW in the lower 48 states (i.e., excluding Alaska and Hawaii). Data collected in AMPD include reported gross generation (in megawatt hours per hour, or MWh/h), steam output (in tons, from combined heat and power facilities), heat input (in million metric British thermal units, or MMBtu), and emissions of sulfur dioxide (SO_2), oxides of nitrogen (NOx), and carbon dioxide (CO_2). Each quarter, CAMD consolidates information from the previous quarter (i.e., there is typically a three-month delay in releasing data) and produces text-based datasets for each of these factors for each fossil-fuel EGU for each state.

Annual hourly capacity factors for utility PV were obtained from the National Renewable Energy Laboratory's PVWatts v.1 tool.[23] Each hourly capacity factor assembled for each AVERT region is based on the average PV capacity factor for four to ten cities in the region. The number and location of the sampled cities were chosen to provide a representative distribution of each AVERT region's insolation (energy from sunlight) at the largest load centers.

Wind capacity factors were developed from annual 6-hour datasets of modeled wind speeds at 80-meter turbine (hub) heights obtained from the Global Model Database developed by AWS Truepower for 2011 through 2013. Depending on the size of the region, between five and 15 locations were used to provide a representative distribution of hypothetical wind turbine installations. Once hourly wind speed data for each site were created by interpolating each of the 6-hour intervals, 2011-2013 hourly wind speed datasets were averaged and were then applied to a power density curve for a Vestas V112 3 MW Wind Turbine. These hourly data were divided by total regional wind nameplate capacity to produce hourly capacity factors. Hourly capacity factor datasets from all sites within a region were then averaged to produce a regional hourly dataset for capacity factors. Further details about the datasets used with the AVERT modules are described in the user manual.[21]

Model Validation

The structure of AVERT includes several unavoidable design limitations, known prior to the development of the model. The three most significant limitations of the model are (a) the ability to model transmission constraints, (b) the departure from operational reality with hard boundaries around regions, and (c) the ability to capture chronological constraints such as minimum downtime or unit commitment constraints. There are three primary impacts of these limitations. First, the location of EE/RE resources cannot be specified with greater geographical precision than at the level of the entire region. Second, the generation avoided by the stimulus can only occur within the boundaries of the specified region. Third, EGU forced and maintenance outages are effectively modeled as de-rates (i.e. a generation reduction, rather than discrete outages). As a part of EPA's peer review, we performed a validation study in order to better understand how results from AVERT compare to those of standard industry models such as ABB's Market Analytics models. The study also highlighted the most appropriate uses of AVERT and the types of questions that AVERT is not best-equipped to answer. As such, a comparative analysis across three distinct levels of geographic resolution was performed to best test the performance of AVERT against an industry standard model, PROSYM. The full validation study will be described in a forthcoming paper, and a summary is provided in Appendix A.

Market Analytics (MA) and other electricity dispatch models provide services that cannot be replicated in the current version of AVERT, such as the ability to forecast and implement different commodity price futures, to alter specific characteristics at existing fossil units (such as heat rates or fuel use), or to implement EE/RE at specific geographic locations with implications for different parts of the grid. However, with caveats made clear, AVERT seems to offer a high level of service for the review of the impact of EE/RE resources on avoided emissions, and appears to provide credible results generally commensurate with MA.

4. CASE STUDY

Description

The capabilities of AVERT to assess the emissions benefits of energy efficiency and renewable energy resources is shown through a select case study, designed explicitly to draw out the unique features of this new tool. The case study demonstrates AVERT's ability to evaluate avoided emissions benefits at the regional, state, and county level across the U.S. It also implicitly highlights the temporal and unit-specific resolution on which the model operates, specifically AVERT's ability to capture the varying degrees of avoided emissions that correspond to different EE/RE resource options within the same AVERT region.

The avoided NO_x and CO_2 emissions effects of four EE/RE resources are compared across AVERT's ten regions, and between each other within a single region, to answer the following questions about the role of electricity-sector EE/RE resources in the U.S.:

- What type of EE/RE resources are most effective at avoiding emissions?
- Are certain EE/RE resources more effective at avoiding NOx or CO_2?
- Are certain U.S. regions more responsive to EE/RE resource options with respect to avoided emissions?
- What is the variation in avoided emissions at the county level?

The four EE/RE resources studied include (a) a portfolio of energy efficiency programs equivalent to a proportional reduction in load in every hour (portfolio EE), (b) a "baseload" energy efficiency program with a constant MWh reduction (baseload EE) (c) a regionally aggregated onshore wind profile, and (d) a regionally aggregated utility solar PV profile. Representative three-day profiles of each of these programs for the MidAtlantic AVERT region are shown in Figure 4, below. Each EE/RE resource represents the same amount of energy overall, or a 3% load reduction.

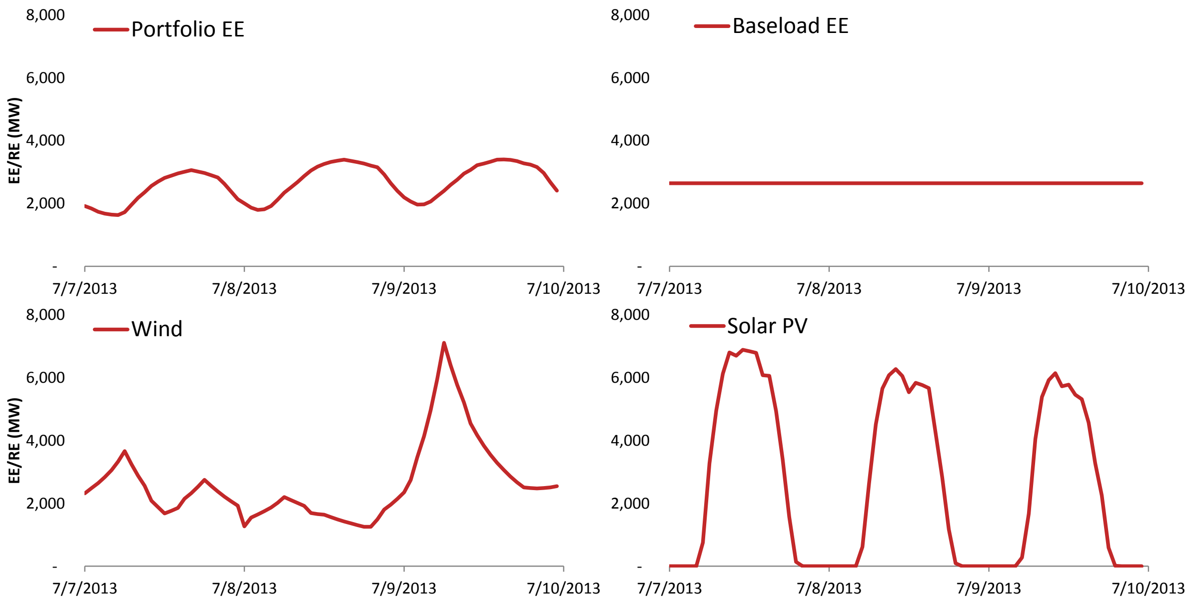

Figure 4. EE/RE resources tested in case study.

The portfolio EE resource is based on the load shape of fossil-fuel generation, and modeled as a fractional reduction in every hour. This option represents a mix of energy efficiency resources that target some or all hours of the year, but preferentially target higher hours with greater demand. The baseload EE resource models a reduction of annual fossil-fuel generation by total megawatt-hours (MWh). This option represents a rough approximation of baseload-only reductions where the total number of MWh reduced over the course of a year is known and is expected to be equally distributed over all hours of the year. Renewable wind and utility solar PV resources are modeled using hourly capacity factors that are broadly representative of the selected region. Given the differences in the underlying energy supply resource base and size of each system, each of the four resource options is modeled as an equivalent % avoided energy (MWh) reduction. A 3% avoided energy equivalent is modeled, as well as sensitivities between 1 and 15%, with a base year of 2013. Results are shown below.

Preliminary Findings and Discussion

<u>Emission benefits across U.S. regions and different EE/RE resource</u>

Table 1 and Table 2 show avoided CO_2 and NO_x emissions, respectively, from the four EE/RE resource options. CO_2 and NO_x emissions are reported as an "avoided emission rate" (avoided tons per avoided MWh and avoided pounds per avoided MWh, respectively) to show results as an emission benefit by mitigation effort. Overall, results for CO_2 show little sensitivity within a region across EE/RE options with respect to avoided emission rates; baseload EE and wind resources net generally higher avoided CO_2 emission rates than utility PV or portfolio EE resources. NO_x emission benefits from EE/RE resources are more varied, as no single resource option maps to highest emission reductions across regions.

Table 1. Avoided CO_2 (tons per MWh) by AVERT region for equivalent 3% avoided generation of an EE/RE resource.

	Wind	Utility PV	Portfolio EE	Baseload EE
Northeast	0.52	0.53	0.54	0.53
Great Lakes / Mid-Atlantic	0.78	0.77	0.77	0.77
Southeast	0.66	0.67	0.67	0.67
Lower Midwest	0.82	0.78	0.79	0.81
Upper Midwest	0.91	0.89	0.89	0.90
Rocky Mountains	0.85	0.83	0.83	0.84
Texas	0.67	0.64	0.64	0.66
Southwest	0.57	0.56	0.56	0.56
Northwest	0.68	0.68	0.66	0.68
California	0.49	0.49	0.49	0.49

Table 2. Avoided NO_x (lbs per MWh) by AVERT region for equivalent 3% avoided generation of an EE/RE resource.

	Wind	Utility PV	Portfolio EE	Baseload EE
Northeast	0.62	0.68	0.72	0.65
Great Lakes / Mid-Atlantic	1.27	1.30	1.31	1.29
Southeast	0.97	1.02	1.02	1.00
Lower Midwest	1.59	1.62	1.61	1.60
Upper Midwest	1.55	1.54	1.54	1.54
Rocky Mountains	1.63	1.56	1.57	1.59
Texas	0.66	0.68	0.68	0.67
Southwest	0.91	0.85	0.79	0.84
Northwest	1.32	1.35	1.38	1.37
California	0.73	0.70	0.67	0.70

Error! Reference source not found.shows the variation in avoided NO_x and CO_2 rates across the country, with the concentration in the Midwest and adjoining regions. Figure 6 shows the underlying electricity supply resource base. For both CO_2 and NOx, higher avoided emission rates from EE/RE appear to be concentrated in the regions with the highest percentage of coal-fired EGUs— Great Lakes/Mid Atlantic (57%), Midwest (48-66%), Rocky Mountain (56%), and Northwest (53%). Broadly, these results match previous studies that have shown EE/RE can avoid significantly more baseload fossil-generation, and therefore emissions, than might be suggested by casual estimates of marginal unit types.[18]

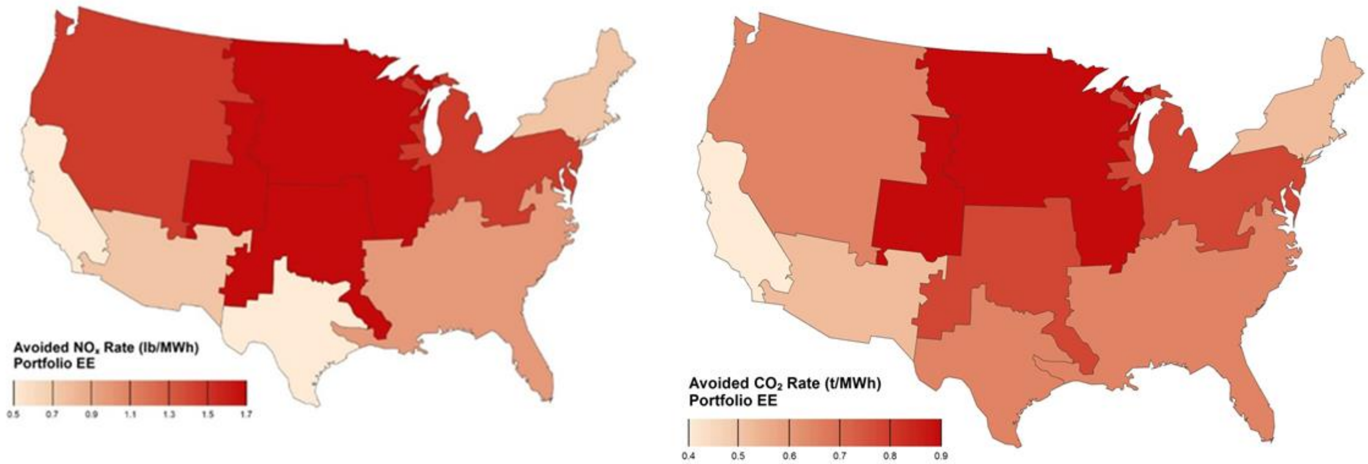

Figure 5. Regional distribution of avoided NOx (left side) and CO2 (right side) (tons per MWh) from a 3% avoided generation portfolio energy efficiency resource.

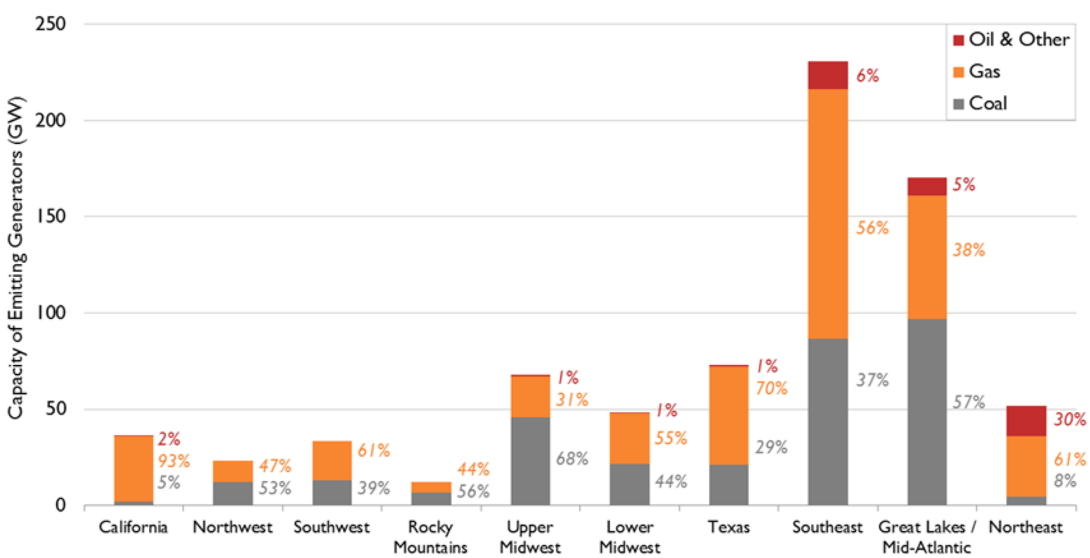

Figure 6. Electricity generation resource base in US regions.

A sensitivity analysis was performed on avoided emissions from a range of penetration levels of portfolio EE (equivalent to between 1% and 15% avoided energy) to explore the robustness of the variation in impact across different regions, and investigate the general magnitude of avoided emissions from increasing levels of energy efficiency. The regional differences in overall impact persist—higher avoided emissions for both NO_x and CO_2 continued to be concentrated in areas with the highest percentage of coal-fired EGUs. However, and more notably, results showed that avoided CO_2 is relatively insensitive to level of energy efficiency, but avoided NO_x is quite sensitive to the level of energy efficiency employed. In many regions, each increment of additional EE/RE has a slightly smaller effectiveness in reducing NOx emissions. A review of the data suggests that the first fraction of EE/RE resources effectively avoid high NOx peaking units; the next increment of EE/RE avoids lower emissions rate intermediate units. The result appears to be consistent with those of studies such as Denny and O'Malley.[19]

County-level NOx emission benefits within one AVERT region

AVERT's unit of analysis is the individual EGU, allowing for a fine resolution in avoided emissions analysis and opportunity to study location(s)-specific origins of avoided generation. County-level emission analysis helps state air quality planners demonstrate that an EE/RE resource is impacting an area that may not be attaining a National Ambient Air Quality Standard. Therefore, here we have also studied avoided NO_x emissions during ozone season at the county-level. Specifically, Figure 7 shows results of county-level avoided NOx emissions from a 3% avoided energy by a portfolio EE resource during ozone season in the Great Lakes-Mid Atlantic region, as well as nearby ozone non-attainment areas (including some outside of the AVERT region). The EGUs in the region are also identified in this map.

The map shows the dispersed nature of county-level effects: emission reductions are widespread throughout the region. However, some individual counties have significant reductions, and non-attainment areas within the region, shown in blue outline, are proximate to some of the highest levels of avoided generation. These county level outputs show how AVERT is uniquely qualified to provide significant value to state and local air quality regulators in assessing options to address Clean Air Act compliance.

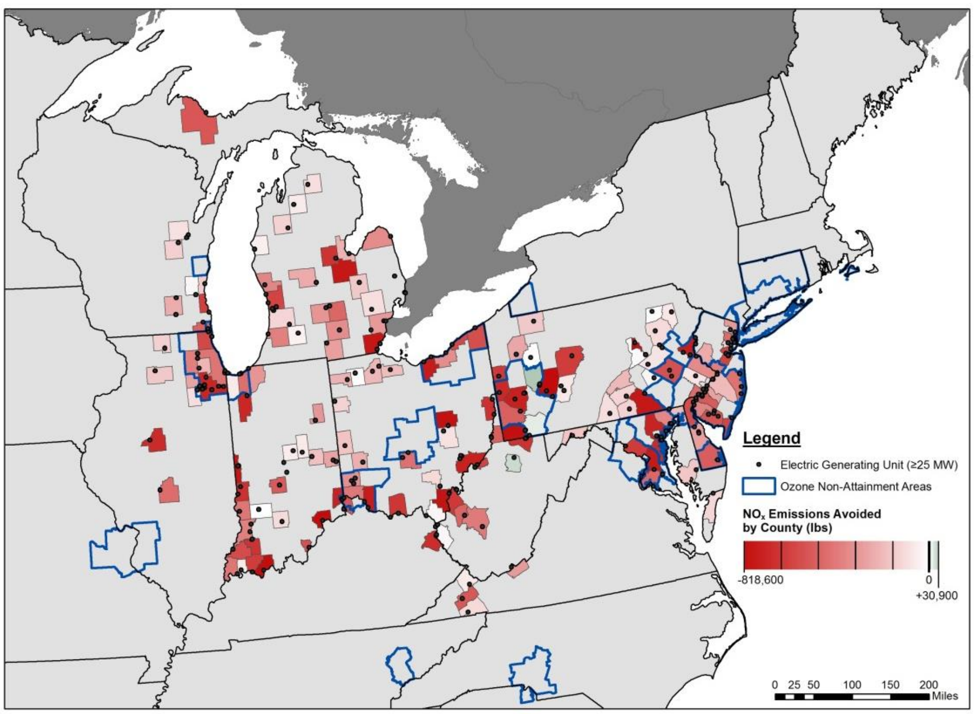

Figure 7. Avoided ozone season NOx emissions in the Great Lakes / Mid-Atlantic region from a 3% avoided generation portfolio energy efficiency program.

5. CONCLUSIONS and DISCUSSION

Summary

The potential to reduce NO_x, SO_2, and CO_2 emissions by avoiding fossil fuel generation poses an important opportunity to states, tribes, and territories for meeting federal, state, tribal, and local Clean Air Act standards through cost-effective and potentially transformative technologies, as opposed (or in addition) to controls at a point-source stack or to boilers. However, these “indirect” emissions reductions are challenging to characterize, and most methods are either inaccessible to policymakers, or operate at a level of aggregation that doesn’t specify localized benefits. Temporal and spatial variation inherent in different EE/RE resources and hourly behaviors of fossil fuel generators do, in fact, affect the avoided emission rates across the US and across different EE/RE technologies. In addition, the ability to localize the multi-pollutant emission reduction within a region can create greater access and utility.

This paper presented a novel methodology embodied in AVERT, to assist regional state and local air quality planners, the U.S. Environmental Protection Agency (EPA), and other stakeholders in estimating avoided NO_x, SO_2,and CO_2 emissions from stationary electric generating units. AVERT is a statistical tool, deriving behavioral characteristics of individual generating units from hourly historical generation and emissions data collected and made publicly available by EPA. While not without its own challenges, the structure of the model avoids several common exogenous assumptions about commonality within blocks of different technologies, pre-determined marginal units, and constant system characteristics during coarsely defined levels of demand. Additionally, AVERT is the first model of its class that has been made publicly available for regulator use for Clean Air Act Plans and industry stakeholders to study different scenarios.

This new tool’s capabilities are demonstrated through a short case study that compared the emissions effects of four different EE/RE resource options—a portfolio of energy efficiency resources, a baseload energy efficiency program, wind, and utility solar PV—across ten U.S. regions. Given the refined temporal and spatial scale in AVERT, the case study also presented a snapshot of results on the proximity of county-level avoided NO_x emissions (from portfolio EE) to EPA’s most recently proposed ozone non-attainment areas in the Great Lakes/Mid-Atlantic region.

Overall, results show that wind and baseload EE resources avoid the greatest levels of CO_2 of the different resource options; but that there is no clear winner across resource options for avoided NO_x. An exploration of the data and temporal patterns suggests that onshore wind and baseload EE resources have proportionally higher generation during off-peak hours, thus preferentially avoid generation at higher CO_2 coal-fired units. Solar and portfolio EE resources, in contrast, target peak hours (on a relative basis) and thus preferentially avoid peaking generation, such as gas units. This pattern is also repeated in the sensitivity analysis, where higher penetrations of energy efficiency tended to have decreasing effectiveness (per increment) in reducing NOx emissions because generation from high NOx peaking units is avoided with increasingly smaller increments of energy efficiency (as generation avoided from more intermediate lower NO_x units increases). This study does not, however, capture unit commitment dynamics wherein more dynamic EE/RE resources (such as wind) may be balanced with additional peaking generation, and thus potentially offset some NOx emissions reductions from avoiding generation at existing resources.

Across regions, areas with higher percentages of coal-fired EGUs had greater NOx and CO2 emissions reductions, per MWh of EE/RE than predominantly gas-fired regions. Finally, the case study illustrated the dispersed and varied nature of county-level effects, and demonstrates the ability for AVERT results to show the proximity of non-attainment areas to some of the highest levels of avoided emissions.

Next Steps

Future research using AVERT will follow two paths: (a) detailed, county or local level air quality modeling, and (b) ongoing improvements and evaluation of the modeling methodology. Immediate next steps involve inquiry into the air quality benefits of renewable energy resources in the Eastern US. AVERT has the capability of producing output files that are compatible with the Sparse Matrix Operator Kernel Emissions (SMOKE) modeling system. SMOKE is designed to create gridded, speciated, hourly emissions for input into advanced air quality models such as the Community Multi-scale Air Quality Model (CMAQ), Regional Modeling System for Aerosols and Deposition (REMSAD), Comprehensive Air Quality Model with Extensions (CAMx), and Urban Airshed Model - Variable Grid (UAM-V). Preliminary results of avoided NO_x emissions in Illinois are shown in Figure 8 below. This research will assess ozone benefits of wind and solar installations within multiple AVERT regions, and project future air quality impacts in 2018 using CMAQ. The ability to assess air quality benefits of avoided emissions further opens up new opportunities for research on the public health impacts of EE/RE resources at spatial and temporal resolutions that have not yet been studied.

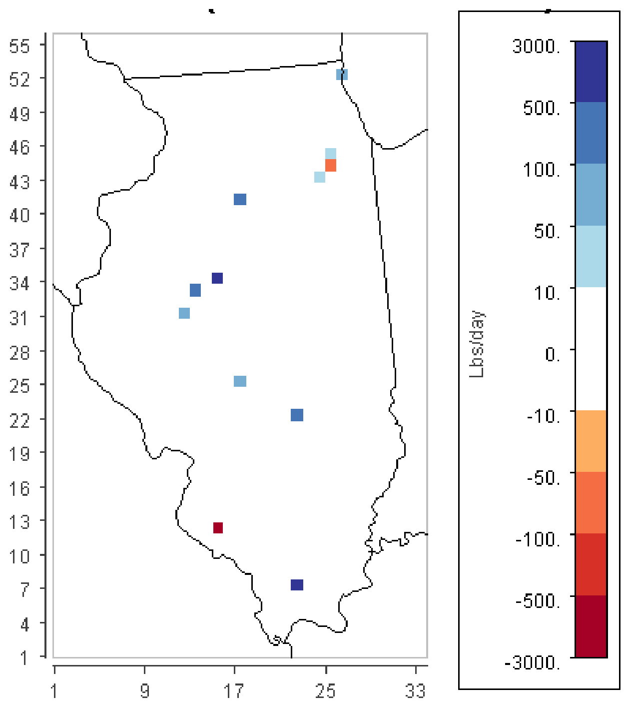

Figure 8. SMOKE model output of county-level avoided NO_x from EE/RE in Illinois.

Ongoing improvements and evaluation of the current modeling methodology will focus on comparing the sensitivity of results from AVERT to other similar statistical methods for calculating avoided emissions that have done so using coarser temporal and/or spatial resolution. The goal is to produce an appropriate level of detail for use in air quality models for the purposes of assessing air and health benefits from EE/RE. As described in the literature review above, other researchers have generated strong results using coarser models, and it will be valuable to understand the tradeoffs between model resolution, insight generated, and level of detail needed for policy decision support. Additionally, the underlying methodology of AVERT is applicable to any geographic location or power system (subject to data availability); using the tool to guide decision making in other regions and countries is an additional valuable line of research.

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APPENDIX A: Validation Study Summary

As a part of EPA's peer review process for AVERT, results from AVERT were compared to those of standard industry models. The study highlighted the most appropriate uses of AVERT, and the types of questions AVERT is not best-equipped to answer. A comparative analysis across three distinct levels of geographic resolution was performed to best test the performance of AVERT against an industry standard model, PROSYM. A detailed description of the full validation process, with extensions, will be presented in a forthcoming paper. This appendix provides a summary of the initial study.

PROSYM is an enterprise-level production cost model engine licensed by ABB on the Market Analytics (MA) platform. The model engine is a commonly used tool within the electric industry, often used to forecast market prices, or anticipate fuel and maintenance expenses. PROSYM solves for optimal dispatch given load requirements, generating unit characteristics, and thermal transmission constraints. The zonal version of the MA platform, used here, divides large regions (in this case, the entire Eastern Interconnect, or "EI") into smaller transmission "zones". These zones represent balancing authority areas usually comprised of one or more load distribution companies (utilities). MA models thermal transmission constraints between zones. Each zone contains both load (customers) and generation (power plants). Transmission zones are modeled as being connected by simple "pipes" that are characterized by the thermal capacity limit and wheeling charges of the aggregate transmission lines between zones.

Identical energy efficiency (EE) resources in similar geographic regions in both AVERT and MA were compared. The EE program modeled was a constant 150-MW reduction in demand in each hour of the year taking place in the PJM region in 2012. In AVERT, the PJM region is broadly contained within the MidAtlantic region, while in MA, PJM is composed of ten smaller zones within the larger EI region. Annual and ozone-season results of these runs were compared in two ways: aggregated across every unit in the entire region for each model (MidAtlantic for AVERT and the EI for MA) and aggregated only across units common to both models. For AVERT, the EE program (the "stimulus") occurred across the MidAtlantic region, and avoided generation and emissions from each generator in the MidAtlantic region were measured. In MA, the entire EI was modeled in each run. The stimulus occurs in one of five particular "stimulus zones" in the PJM region and avoided generation and emissions is measured from generators across the entire EI. The impact of identical EE resources implemented in Ohio, Eastern Pennsylvania, Kentucky / Ohio, Chicago, and New Jersey were compared.

The results from the MA model across the EI vary by stimulus zone, but in all cases capture avoided generation within 5% of the anticipated result. Variation may be due to transmission losses. Restricting the analysis to review only the units in common between the two models that are within PJM, the fuel mix of avoided generation shifted towards more avoided coal in both models, and the models were in closer agreement. Finally, when examining the outcome of MA and AVERT for PJM units that are common to both models, but in the ozone season only, results displayed close agreement again. The geographic patterns remain similar in the analyses restricted to the units in common. The benchmarking study indicates that AVERT and MA are in close agreement when stimulus zones are near the center of AVERT regions, but diverge when stimulus zones are near the edges of AVERT boundaries. The MA analysis also indicated that EE/RE impacts may be spread across a large area of the Eastern Interconnect.

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