The air quality and human health effects of integrating utility-scale batteries into the New York State electricity grid

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Abstract

In a restructured electricity market, utility-scale energy storage technologies such as advanced batteries can generate revenue through energy arbitrage by charging when prices are low and discharging when electricity prices are high. This strategy also changes the magnitude and distribution of air quality emissions, ambient concentrations, human health effects and social costs and benefits. We evaluate these effects with a case study of 500 MW sodium-sulfur battery installations with 80% roundtrip efficiency displacing peak electricity generators in New York City from 1 – 5 pm and charging using off-peak generation in the New York Independent System Operator (NYISO) electricity grid from 1 – 6 am during summer. First, we map displaced and charging plant types to generators in the NYISO. Second, we convert the changes in emissions into ambient concentrations with a chemical transport model, the Particulate Matter Comprehensive Air Quality Model with extensions ($PMCAM_x$). Finally, we transform the concentrations into their equivalent human health effects and social benefits and costs. Focusing on the relationship between premature mortality and fine particulate matter ($PM_{2.5}$), we calculate a benefit of 4.5 ¢/kWh and 17 ¢/kWh from displacing a natural gas and distillate fuel oil fueled peaking plant, respectively, in New York City. By contrast, ozone (O_3) concentrations increase due to the decrease in nitrogen oxide (NO_x) emissions, although the magnitude of the social cost is less certain. Adding the air quality costs from charging, we find that displacing a distillate fuel oil peaking plant yields a net social benefit, while displacing the natural gas peaking plant has a net social cost. Additionally, by using the present base-load capacity for charging, the upstate population experiences an increase in adverse health effects. If wind generation is utilized to charge the battery, both the upstate charging location and New York City would benefit.

Keywords: electric energy storage, emissions, ambient air quality, human health costs

1. Introduction

Electric energy storage (EES) can decouple the time of electricity generation from its consumption, by storing electricity or energy to provide electricity when needed [1]. This can provide a range of benefits including reducing the need for new electricity generation capacity to meet peak electricity demand, relieving strain on transmission and distribution (T&D) infrastructure and supporting variable renewable sources such as wind [2, 3]. Another benefit of EES installations is that they are easier to site than conventional power plants, allowing them to be located where electricity and generation capacity is most valuable. For example, Walawalkar et al. (2007) examined the revenue opportunities for a sodium-sulfur (NaS) battery in the New York Independent System Operator (NYISO) electricity markets. Using optimistic assumptions about the capital cost, Walawalkar et al. (2007) found the battery could operate profitably 65% of the time in New York City through energy arbitrage and by participating in the installed capacity market which provides additional revenue for having available generation [4]. Presently, the capital costs almost double those assumed in Walawalkar (2007); however, given the revenue opportunities in NYC, this would be an attractive site if the capital costs decrease, since energy arbitrage revenues are high there. One reason these facilities may experience fewer barriers to siting is that the batteries have no emissions. This could be especially beneficial in highly populated urban load centers where the battery would displace dirtier generators, known as peaker plants, installed to meet peak electricity demand [5]. Depending on the location and type of generator used to charge the battery and the generator displaced by the battery, however, there may be net positive or negative social costs in terms of air quality, exposure and human health. In addition, there are also equity concerns about shifting emissions from one location to another.

Previous studies investigating how EES facilities would interact with existing generation capacity and the resulting effect on air quality have produced mixed results. Restricting their analysis to the change in total emissions, Denholm and Holloway (2005) investigated a system composed of a new non-adiabatic compressed air energy storage (CAES) charged with existing older coal-fired generators. They found that the storage device does not bring the generator into compliance with New Source Performance Standards (USEPA) [6]. Total emissions, however, does not account for the changes in the spatial and temporal distribution caused by charging and discharging the battery. Emissions must also be converted to their equivalent ambient concentrations before they can be used to characterize exposure or allow for the quantification of human health effects. Finally, emissions analysis cannot account for the most pernicious pollutants with respect to human health, ozone (O_3) and particulate matter with aerodynamic diameter less than 2.5 μm or fine particulate matter ($PM_{2.5}$), which are formed as a result of chemical reactions of the directly emitted chemical species [7].

The most comprehensive tool for converting emissions to ambient concentrations is a chemical transport model (CTM). CTMs have been widely employed to predict changes in air quality from distributed generation (DG) on the same scale as utility-size batteries. For example, Gilmore et al. (2006) evaluated the air quality effects of using diesel generators with and without emission controls for meeting peak electricity demand in New York City [8]. Similarly, Rodriguez et al. (2006) employed a CTM to evaluate the change in ambient air quality from introducing varying amounts of different forms of DG into California. Depending on the magnitude, location and type of DG, they found decreases and increases in ambient concentrations of O_3 and $PM_{2.5}$ [9]. Carreras-Sospedra et al. (2008) ran similar scenarios in the Northeast United States, but retired older base load generation such as pulverized coal plants [10]. By contrast to Rodriguez et al. (2006), O_3 and $PM_{2.5}$ decreased in these scenarios. To the best of our knowledge, there has been no study which has used CTMs to evaluate the air quality effect of integrating EES into electricity grids.

In this paper, we isolate the changes in air quality and human health effects by modeling a single NaS battery (or a number of NaS installations) located in New York City, charging with off peak base-load resources in the New York Independent System Operator (NYISO) region. First, we evaluate the net costs or benefits of changes in air quality and human health effects for combining the battery with individual charging plants that exist in the NYISO as well as new generation such as wind capacity. Second, we calculate the costs and benefits at the system-level by developing estimates of the frequency that each type of plant would be used for charging. Finally, we investigate the distribution of the costs and benefits in the NYISO area. We consider the social cost from changes in health effects only and do not include other potential social costs and benefits such as reducing peak electricity prices. We conduct the air quality modeling with a 'state of science' chemical transport model, the Particulate Matter Comprehensive Air Quality Model with extensions ($PMCAM_x$) [11].

2. Methods and data

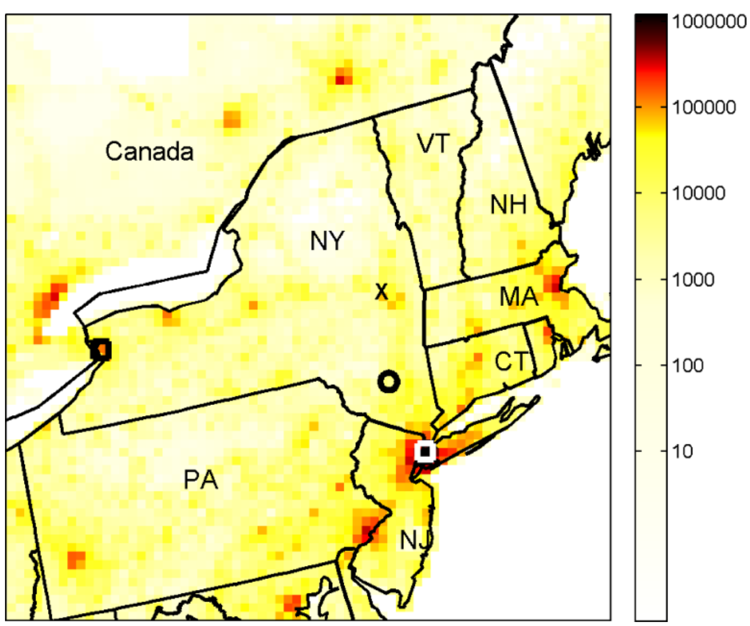
For our case study, we site a 500 MW NaS battery facility (or 500 MW of cumulative battery installations) in New York City, New York. Consistent with the market analysis of Walawalkar et al. (2007), we assume that the battery is operated to maximize revenue, discharging from 1 – 5 pm and charging from 1 – 6 am (Eastern Standard Time) during summer. The additional hour of charging time is required to account for the battery round-trip charging efficiency of 80%. This scenario results in 2,000 MWh (500 MW x 4 hours) of electricity provided per day by the battery. This configuration is important since New York City is highly populated, and there is a wide range of generators that could be used for charging in the NYISO region.

2.1 Charging and displaced plants

First, we develop a list the potential power plant types used for charging and plants displaced by the battery. We map these plant types to indicative facilities in the NYISO as shown in Figure 1. Coordinates for these facilities are obtained from the Facility Registry Service (FRS) managed by the USEPA [12].

While the NYISO has information on the actual charging and displaced plants, it does not release this data publicly. Since we cannot restrict the types of charging plants, we investigate the effect of coupling the battery with a range of different fuel-generator types available in NYISO. These plants are taken from the list in the US Environmental Protection Agency's Emissions & Generation Resource Integrated Database, 2006 (eGRID) [13]. We identify four candidate plant types: a pulverized coal plant, natural gas (NG) fueled combined cycle turbine, a residual fuel oil (RFO) fueled boiler-steam turbine, and a NG fueled boiler-steam turbine. To bound the effect of a coal plant, we model a plant without any emission controls as well as a plant with modern emission controls. In New York, coal plants have modern emission controls as a result of legal settlements to a New York State lawsuit against dirtier coal plants in 2005 [14]. For the NG and RFO fueled charging plants, we also model the possibility that the charging plant is co-located the plant with the battery in New York City. We do not consider nuclear or hydro-electric facilities as they are not marginal plants in the NYISO system at night during the summer. These plants are classified as must-run plants, and the minimum load during the summer months in New York State exceeds their combined capacity.

Figure 1: Location of charging and displaced generators. The coal plants are modeled at the outlined black square in Western New York State. The natural gas fueled combined cycle turbine is modeled at the cross. The residual fuel oil or natural gas boiler-steam turbine is located at the black circle. The battery displacing the natural gas or distillate fuel oil peaking turbine is located in New York City, shown at the outlined white square. A charging plant, either a natural gas or residual fuel oil boiler-steam turbine, may also be located in New York City. Population per 12 km by 12 km grid cell is shown. CT = Connecticut, MA = Massachusetts, NH = New Hampshire, NJ = New Jersey, NY = New York, PA = Pennsylvania and VT = Vermont.



In addition to the existing plant types, we evaluate two long-run possibilities for the charging plant. First, we model a coal plant as an integrated gas combined cycle (IGCC) facility. This facility would reduce emissions in a manner consistent with an emission-based air quality rule such as the USEPA Clean Air Interstate Rule (CAIR) [15]. Under this type of regulation, the total emissions of a given pollutant (e.g. nitrogen oxides, NO_x or sulfur dioxide, SO_2) are capped, and each generator must procure sufficient credits to cover its emissions [16]. Facing a shortfall, a generator can purchase additional credits from another generator which has reduced its emissions or it can reduce its own emissions by emission controls or other modifications to the facility. Under some circumstances, it may become uneconomical for the generator to continue to operate. We limit our modeling to a generator which chooses to reduce its emissions. Second, we model base-load wind as the marginal plant. The New York Renewable Portfolio Standard (RPS) mandates that renewable sources provide 25% of electricity in 2013 [17]. It is expected that 4.7% will be met by new generation and that substantial amounts of wind generation will be installed [18].

We assume that the battery would displace a simple cycle turbine (peaking plant) located in New York City. In New York, many of these peaking plants are subject to the Minimum Oil Burn reliability rule which requires that they operate on a minimum level of a fuel other than NG during periods of high demand [19]; this is generally distillate fuel oil (DFO). Since we are unable to determine whether the peaking plant is operating on NG or DFO, we model both a NG and DFO simple cycle turbine. In some cases, upstate generators also provide peak electricity. We do not evaluate the potential that upstate generators would also be displaced by the battery, and as such, we do not model potential benefits from avoided thermal transmission loss (although any thermal benefits would likely be offset by battery inefficiency).

2.2 Air quality modeling and emission factors

To model the air quality effects, we develop emission factors (EF) and heat rates (efficiency) for each fuel-generator type. Emission factors measure the amount of a pollutant released (in grams) per unit of electricity generated (in kilowatt-hours, kWh). These EFs and heat rates can vary significantly for any given fuel type, depending on plant configuration, operating conditions, and emission control technologies. In Table 1, we present the EFs (in g/kWh) and heat rates (in Btu/kWh) used in this work. The EFs in this work are derived from the USEPA AP-42 compilation [20], the observed values for NYISO generators in eGRID [13] and the Integrated Environmental Control Model (IECM) for coal [21]. Heat rates are derived from observed values for NYISO generators in eGRID and Graus et al. (2007) [22]. For the coal plants, we model three different configurations with IECM: a coal plant without emission controls, a plant with modern emission controls, and an IGCC. We specify a bituminous coal consistent with the quality of coal delivered for electricity generation in New York State with 8.1 % ash and 2.2 % sulfur [23]. For the plant with emission controls, we add an electrostatic precipitator (ESP) to reduce $PM_{2.5}$, flue gas desulfurization (FGD) to reduce SO_2 and selective catalytic reduction (SCR) to reduce NO_x. With the possibility of regulations restricting carbon dioxide (CO_2) emissions, some new coal plants may be constructed with carbon capture and storage CO_2 emission controls. We do not model CO_2 emission controls on any plants.

The EFs from Table 1 are split into species consistent with the representation in $PMCAM_x$. The NO_x emissions are split into 85% nitrogen oxide (NO) and 15% nitrogen dioxide (NO_2). The $PM_{2.5}$ mass is split equally into elemental (EC) and organic (OC) carbon. The $PM_{2.5}$ mass is also separated over six size bins representing aerodynamic diameter less than 2.5 μm. The total emissions are calculated by multiplying the speciated EF by the amount of electricity generated (i.e., 2,000 MWh per day for the displaced plant and 2,500 MWh per day for the charging plant). We allocate these emissions to the appropriate hours and plant locations. Since the emissions are based on literature and average values rather than emissions specific to that plant, the results should not be interpreted as the actual effect of altering emissions at the actual plant. Rather, these results are broadly indicative of the emissions from each plant type. We consider only emissions associated with electricity generation.

To transform the total emissions to ambient concentrations, we employ the Particulate Matter Comprehensive Air Quality Model with extensions ($PMCAM_x$). $PMCAM_x$ is a 'state of science' CTM that simulates the emission, advection (convection), dispersion, gas and aqueous phase chemical reactions, and dry and wet deposition for 35 gaseous species, 12 radical species and 13 aerosol species in 10 size bins on a 3-D Eulerian grid. Additional modules simulate the dynamic behavior (coagulation, condensation, and nucleation) of aerosols species. Details and evaluation of the model can be found in Gaydos et al. (2007) [11] and Karydis et al. (2008) [24]. We model the ambient air quality concentrations for each charge-displace combination for a period of two weeks in July 2001 (July 15 – 28), corresponding to a period when $PMCAM_x$ has been extensively evaluated. We present our results as the average ambient concentration over this two week period. We interpolate the available meteorological fields produced by the mesoscale model, known as MM5 [25], and the baseline emission files from the Lake Michigan Air Directors Consortium (LADCO) [26] from a 36 km horizontal grid resolution to a 12 km grid to resolve better the change in emissions and the resulting concentrations. The vertical grid is discretized into 14 layers from the surface to 6 km. The lowest model layer is slightly less than 30 m thick vertically. For the coal plant, the emissions are modeled as emitted into the second layer from the ground. Emissions from all other plants are modeled as emitted into the first layer. This is consistent with the stack heights of these facilities.

Table 1: Emission factors in g/kWh and the heat rate in Btu/kWh for plant types [13, 20, 21, 22]

Plant Type	**Nitrogen Oxides (NO_x) (g/kWh)**	**Sulfur Dioxide (SO_2) (g/kWh)**	**Fine particulate matter ($PM_{2.5}$) (g/kWh)**	**Heat Rate (Btu/kWh)**
Uncontrolled pulverized coal	2.20	2.66	0.582	10,400
Controlled pulverized coal	0.70	1.10	0.058	10,200
IGCC coal	0.45	0.23	0.038	9,900
RFO boiler	1.00	2.35	0.139	11,700
NG boiler	0.67	~0	0.037	11,700
DFO turbine	1.53	0.093	0.158	12,500
NG turbine (simple cycle)	1.31	~0	0.036	12,500
NG turbine (combined cycle - NGCC)	0.186	~0	0.023	6,900

2.3 Human health effects and social costs

We evaluate the human health effects for each separate charging plant and displaced plant, for each potential charge-displace combination, and for the entire system (i.e. accounting for the frequency that each plant is used for charging). The social value is generated by translating the changes in ambient air quality into morbidity and mortality effects and then to a dollar value associated with these effects using concentration-response (CR) functions and "willingness to pay (WTP)", as shown in Eq (1).

We express the resulting social cost or benefit as a value normalized by the electricity provided by the battery (e.g. 2,000 MWh per day).

$$SC = \sum_{i=1}^{n} [1 - \exp(-\beta_i \cdot \Delta conc)] \cdot pop \cdot y_o \cdot WTP_i \qquad \text{... Eq. (1)}$$

Where i is each different health endpoint;

n is the total number of different health endpoints;

β is the strength of the relationship between the change in ambient concentration of a given pollutant and the endpoint (in cases per 24-hour average ppb or cases per 24-hour average $\mu g/m^3$);

Δconc is the change in ambient concentration of a given pollutant (in 24-hour average ppb or 24-hour average $\mu g/m^3$);

pop is the population exposed to the change in concentration;

SC is the social cost (in $);

WTP is the "willingness to pay" to avoid the adverse health effect (in $); and,

y_o is the baseline incidence of the adverse health effect in the absence of the pollutant.

We use βs, WTPs, y_o, and population distribution from the Environmental Benefits Mapping and Analysis Program (BenMap), version 2.4.85 [27]. We also extend the BenMap population and incidence values to include Canada with population from the Gridded Population of the World dataset [28]. We focus on change to premature mortality from O_3 and $PM_{2.5}$. A range of morbidity effects such as respiratory and cardiovascular events and reduced activity days are also associated with changes in air quality, but previous studies have found that these contribute less than 15% to the overall social cost [29, 30].

To evaluate mortality due to changes in O_3, we use a 24-hour averaging metric from Bell et al. (2004), (2005) and (2006) [31-33]. To evaluate the long term (annual) effects of $PM_{2.5}$ and mortality, we use a fixed pooling of CR relationships from Pope et al. (2002) [34] and Laden et al. (2006) [35]. We assume that the average of our 14 modeled days is representative of the change in ambient concentrations that would be observed on any given summer time day. We restrict our analysis to the summer as previous analysis found that the battery will derive most of its revenue in the NYISO summer capability period from May 1st – October 31st [4]. To convert premature mortality into dollars, we model the value of a statistical life (VSL) as a Weibull distribution with a mean of $7.5 million (in 2005 dollars) (Weibell scale parameter: $8,300,000; Weibull shape parameter: 1.5096). We also show 5% and 95% confidence intervals to capture the uncertainty in the health endpoints and WTP estimates.

In addition to calculating the cost of the change in human health effects for the separate charging and displaced plants and for the charge-displace combinations, we are also interested in evaluating the overall social cost of operation for the system. This requires multiplying the social value of each possible charge plant and the each possible displaced plant by the frequency with which that plant type is employed as shown in Eq (2).

$$\text{Overall Efficiency} = \sum_{1}^{j} SC_j \cdot XMP_j + \sum_{1}^{k} SC_k \cdot XMP_k \qquad \text{... Eq. (2)}$$

Where j is the number of possible charging plants;

k is the number of possible displaced plants;

SC is the social cost for each plant used for charging or is displaced (in \$); and

XMP is the fraction that each plant type is used for charging or displaced.

As mentioned in section 1.2.1, the NYISO does not release information about the fuel or plant type on the margin. We review the available data and provide details on the development of our independent estimates in Appendix A. While we cannot derive conclusive frequencies, we find that eGRID can be used for preliminary estimates.

3. Results and discussion

3.1 Ambient air quality concentrations

In Figure 2, we show the average change in concentration for $PM_{2.5}$ in µg/m^3 over the two week simulation for displacing a DFO peaking turbine in New York City. As expected, the changes in ambient air quality are small for one 500 MW battery. However, if 10-20% of peak load in New

York City were handled by batteries, the observed changes in air quality would be much larger. Small decreases in $PM_{2.5}$ are observed due to a reduction in primary emissions with very small changes in the portion of $PM_{2.5}$ (secondary) that is formed by reactions of gases. In Figure 3, we show the average change in concentrations of O_3 in ppb over the two simulation weeks. Small increases in O_3 are observed. These O_3 increases are consistent with the VOC to NO_x ratios predicted by $PMCAM_x$. When the initial ratio of NO_x to VOC is high (i.e., VOC-limited), adding more NO_x will decrease the formation of O_3. At lower ratios (i.e., NO_x-limited), the additional NO_x increases the formation of O_3. Urban centers tend to have high NO_x to VOC ratios, and hence, adding more NO_x leads to the observed increases [36]. Compared to displacing a DFO fueled turbine, a NG turbine yields the same spatial patterns for both O_3 and $PM_{2.5}$ with the magnitude of the change reduced by the difference in the emissions between the two turbines. Differences in wind patterns over the two-week modeling period account for the cloud of ambient concentrations for both $PM_{2.5}$ and O_3.

We show the average change in the concentration of $PM_{2.5}$ in $\mu g/m^3$ for an uncontrolled coal plant and for RFO boiler-steam turbine plant in Figure 4 and Figure 5, respectively. For $PM_{2.5}$, we observe small increases. We show the average change in concentrations of O_3 in ppb over the two simulation week for an uncontrolled coal plant (Figure S1) and for a RFO boiler-steam turbine plant (Figure S2) in the Supplementary Material. For O_3, we observe both increases and decreases consistent with the modeled VOC/NO_x ratios. For a coal plant with emission controls and the IGCC, we observe the same spatial patterns for both O_3 and $PM_{2.5}$ as the uncontrolled coal plant. Similarly, we observe the same spatial patterns for a NG boiler-steam turbine plant as the RFO boiler. The change in ambient concentrations for the NG combined cycle plant is not shown since only very small changes are observed.

Figure 2: Change in daily mean $PM_{2.5}$ in μg/m^3 concentrations as an average of two weeks of simulation for displacing a DFO peaking turbine in New York City. The wind patterns account for the cloud of ambient concentrations. The white box shows the location of New York City. CT = Connecticut, NJ = New Jersey, NY = New York, and PA = Pennsylvania.

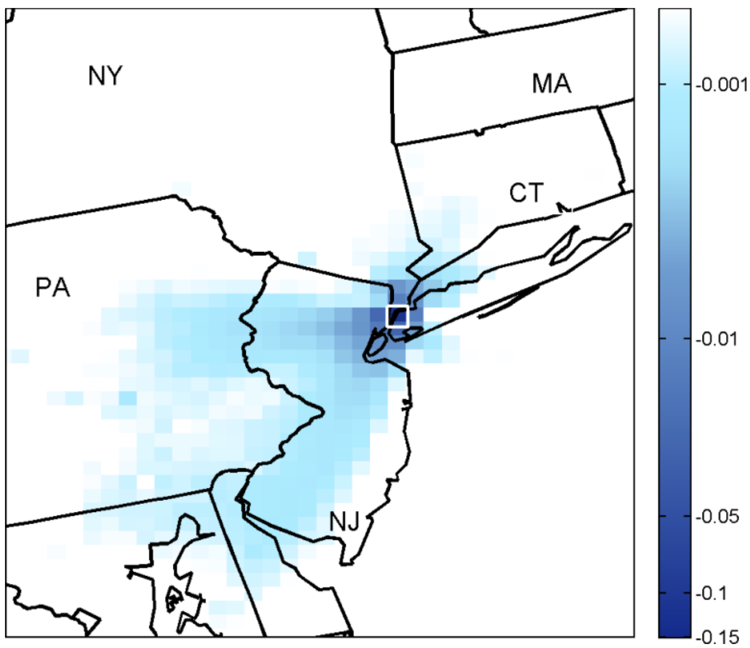


Figure 3: Change in daily mean O_3 in ppb concentrations as an average of two weeks of simulation for displacing a DFO peaking turbine in New York City. The wind patterns account for the cloud of ambient concentrations. The white box shows the location of New York City. CT = Connecticut, MA = Massachusetts, NJ = New Jersey, NY = New York, and PA = Pennsylvania.

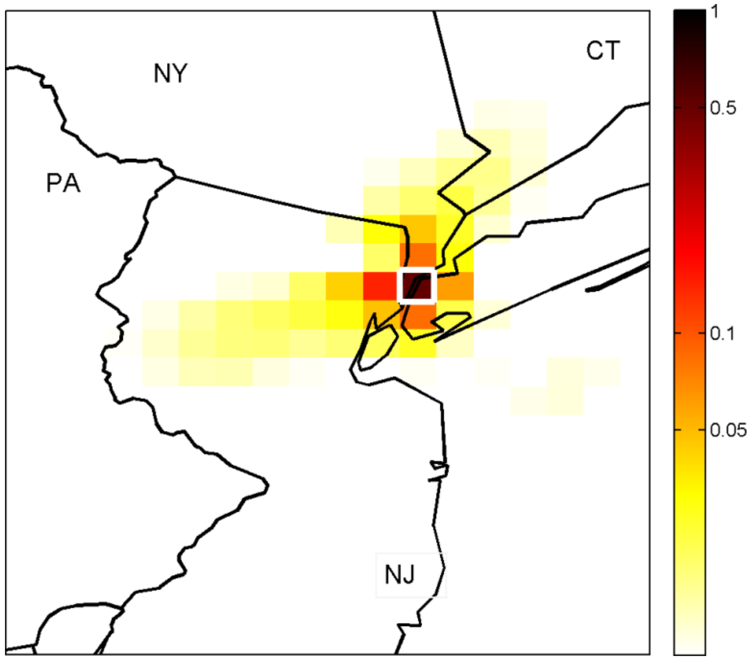


Figure 4: Change in daily mean $PM_{2.5}$ in μg/m^3 concentrations as an average of two weeks of simulation for charging with an uncontrolled coal plant. The wind patterns account for the cloud of ambient concentrations. NY = New York.

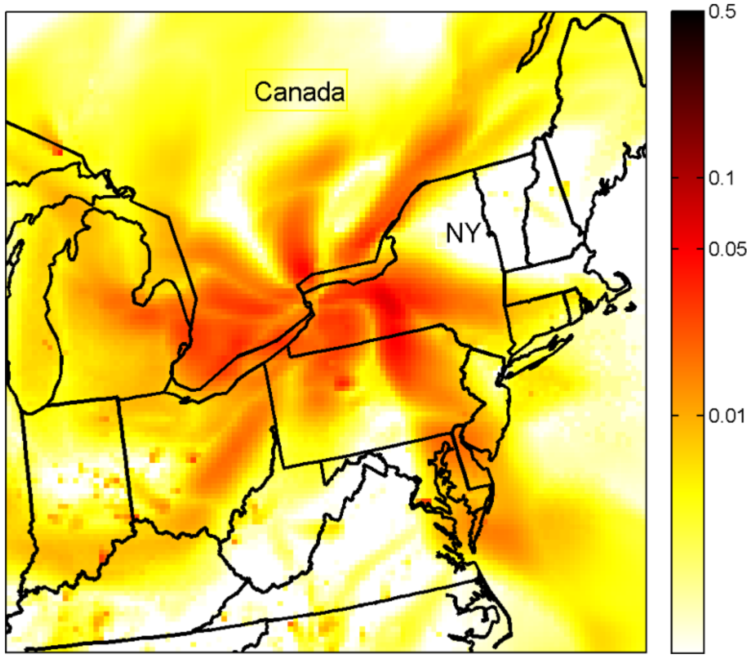
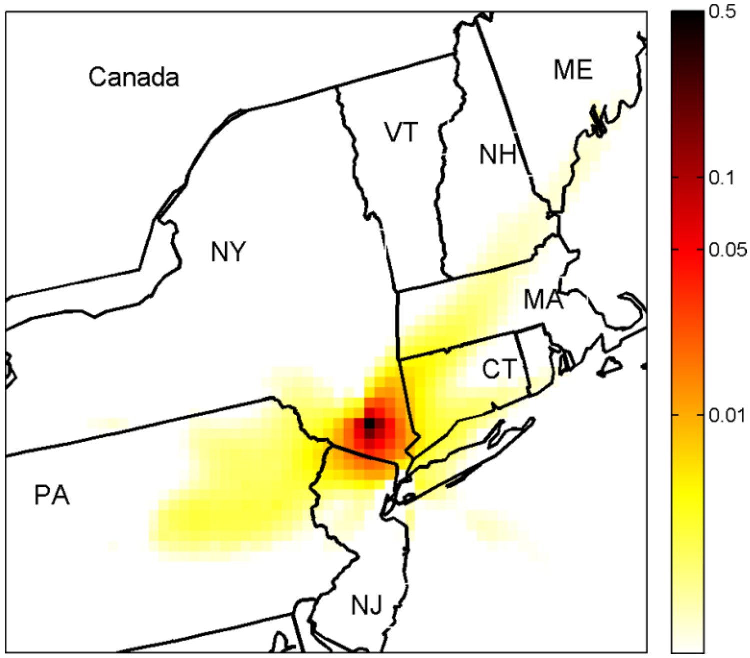


Figure 5: Change in daily mean $PM_{2.5}$ in μg/m^3 concentrations as an average of two weeks of simulation for charging with an RFO boiler-steam turbine plant. The wind patterns account for the cloud of ambient concentrations. NY = New York.



3.2 Human health effects and social costs

In Figure 6 and Figure 7, we show the social costs from mortality from $PM_{2.5}$ for each charge-displace plant combination for displacing a DFO and NG peaking turbine, respectively. The values calculated in this work are slightly higher than other CR type studies [37], but are within the range of values from the European ExternE project [7, 38]. The higher values in ExternE are the result of denser populations in parts of Europe; these population densities are consistent with the population in the New York City region. Our values are also slightly higher as we are normalizing the social values over the amount of electricity discharged by the battery rather than the amount of electricity used for charging (e.g. 2,000 MW rather than 2,500 MW). These values with the 5% and 95% confidence intervals for $PM_{2.5}$ and O_3 are tabulated in Table S1 in the Supplementary Material.

The health benefits from reducing $PM_{2.5}$ are well established. For the New York City region, we observe a social benefit from reducing $PM_{2.5}$. Adding the costs from increases in $PM_{2.5}$ associated with the charging plant, we still observe social benefits for displacing a DFO unless an uncontrolled coal plant or a RFO boiler located in New York City is used for charging. For displacing a NG peaking plant, we find a social benefit only if cleaner generators are used for charging such as natural gas fueled generators and controlled coal plants.

We also evaluate the changes in mortality from O_3. The increases in O_3 from displacing a peaking plant in New York City leads to a social cost from increased mortality. These social costs decrease the benefit from reducing $PM_{2.5}$. For displacing a NG peaking plant, summing the social value from changes in mortality for $PM_{2.5}$ and O_3 results in a net social cost for all possible charging plants. While the relationship between exposure to $PM_{2.5}$ and premature mortality is relatively well understood, the magnitude of relationship between mortality and O_3 is subject to greater uncertainty [30]. As a result, we caution against a simplistic summing of O_3 and $PM_{2.5}$ social costs.

In addition to the social costs and benefits for each charge-displace combination, we also calculate the total system social cost for the battery. In Appendix A, we evaluate the existing publicly available data and deem it insufficient to allow us to perform more than a rough estimate of the dispatch frequencies that we show in Table A1. We find that there are a number of plants that operate on both NG and RFO. We evaluate a condition where all of these dual fuel (DF) plants operate on NG and where all of the DF plants operate on RFO. Using these frequency estimates, we find an overall social benefit when a DFO peaking plant is displaced for mortality from $PM_{2.5}$ only and the sum of mortality from $PM_{2.5}$ and O_3. If a cleaner NG peaking plant is displaced, system social cost rises in almost all cases unless all DF plants are operating on NG.

Figure 6: Net social cost for $PM_{2.5}$ for displacing a DFO peaking plant in ¢/kWh. The dark grey bars are the separate charge-displace combinations. The light grey bars are for different system-level charging plant combinations. DF indicates the type of fuel that is being used by a dual fuel charging plant (e.g. natural gas, NG, or residual fuel oil, RFO). NYC indicates that the charging plant is located in New York City.

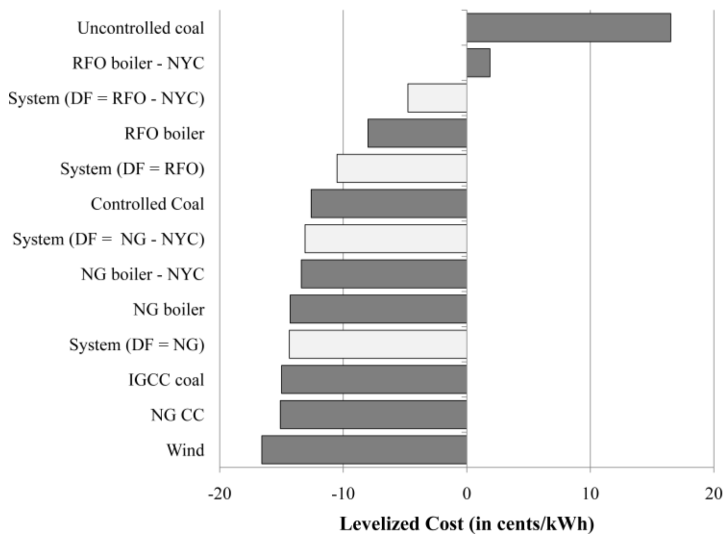
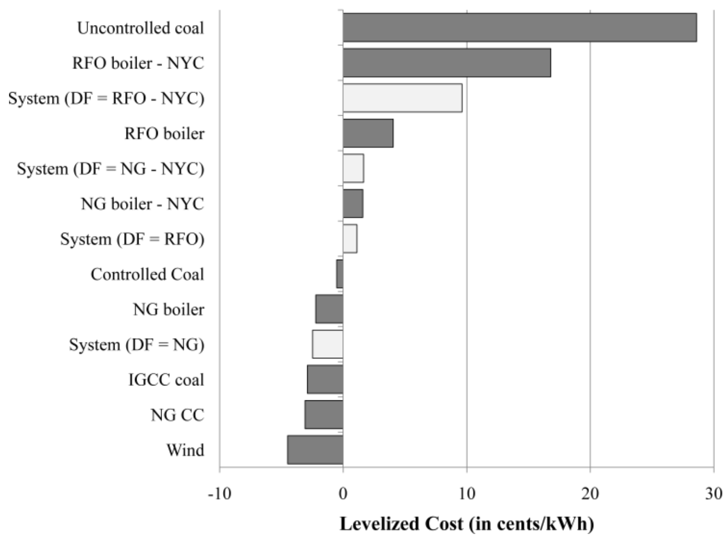


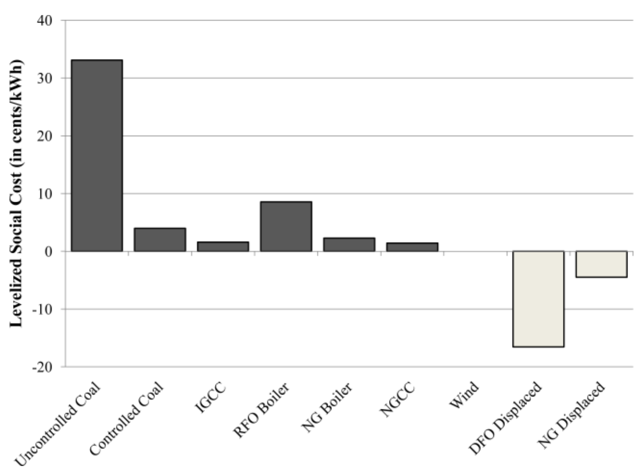
Figure 7: Net social cost for $PM_{2.5}$ for displacing a NG peaking plant in ¢/kWh. The dark grey bars are the separate charge-displace combinations. The light grey bars are for different system-level charging plant combinations. DF indicates the type of fuel that is being used by a dual fuel charging plant (e.g. natural gas, NG, or residual fuel oil, RFO). NYC indicates that the charging plant is located in New York City.



In this analysis, we use average values for heat rate and full-load emissions factors. Some generators, however, would be operating at partial load during off peak periods [6]. Since most generators operate more efficiently at full-load conditions (e.g. lower average heat rate), the additional demand for charging the battery could potentially decrease the air quality emissions per kWh generated from these plants. Thus, this analysis may lead to an overestimation of the cost of integrating a battery in NYISO. Again, better information about the dispatch order of the plants would be necessary to identify a plant operating at partial load.

We also separate the social cost of $PM_{2.5}$ into the charging and displaced portions to evaluate the distribution of the benefits and costs. We show the results in Figure 8. In all cases except wind, a population located in the upstate portion of New York state experiences deterioration of ambient air quality and adverse human health effects. For charging plants located upstate, New York City may also experience a change in ambient concentrations. We find that this effect is small unless the charging plant is co-located with the battery; as a result, we do not separate the charging and discharging components for a co-located charging plant. In the case of the charging plant being co-located in NYC, the cost is imposed on the same population that observes the benefit from displacing peaking generation, reducing equity concerns.

Figure 8: The social costs for $PM_{2.5}$ for the charging generator and displaced peaking plant in ¢/kWh. The dark grey bars are the social costs from charging the battery. The light grey bars are the social benefit from displacing the peaking plant in New York City.



If we consider only short-term effects (e.g. using existing NYISO generators), therefore, there are important distributional effects. In the long-term, the battery will also interact with new generation capacity and regulations affecting the electricity sector. Under a rule similar to CAIR, operating any of the charging plants may require the purchase of additional emission credits. If emissions allowances are purchased (assuming that no party is using banked allowances), then a reduction in emissions must be observed in another location. Since the premise of emission trading is that each generator in the trading group has emissions with approximately equal social cost [16], these trades should result in a net zero change in social cost. These benefits, however, may or may not accrue to the New York State populace depending on the location of the generator that sells the credits. It is outside the scope of this paper to evaluate potential trades. We do, however, investigate shifting the coal plant to an IGCC as a response to CAIR. We find that the IGCC has a significant benefit, reducing the social costs from charging to values in the same range as NG fueled options. The battery installation can also interact and support intermittent renewable resources. At the end of 2008, there was approximately 1.15 GW of installed wind capacity in New York State with a doubling expected in the next several years as a result of the RPS [39, 40]. If wind is the charging plant, there could be no effect on the population at the charging location. In addition to cleaner charging plants, the IGCC and the wind turbines have the additional benefit of reducing the social cost for all electricity that is generated from that plant.

4. Conclusions

Depending on the charging plant and the displaced plant, there is a potential for a social cost or benefit from integrating battery storage into the NYISO. If dirtier in-city peaking plants are displaced by the battery and cleaner upstate facilities such as NG combined cycle plants are used for charging, a social benefit results. However, if NG peaking plants are displaced in New York City, there may be a social cost from charging with existing base load generation with higher emissions in the NYISO such as a RFO fueled boiler. Increases in O_3 in New York City from displacing the NO_x emissions from either a DFO or NG peaking plant also raise potential health concerns. We note, however, that the USEPA has promulgated progressively more stringent air quality standards affecting electricity generation. As a result, we expect that there will be more scenarios where the benefit from displacing peaking plants in the highly populated New York City will exceed the reduction in air quality costs from the charging plant.

Regardless of the overall value for a charge-displace combination, additional pollution emissions may create an equity concern for the upstate population. Emissions trading under a rule such as CAIR might alleviate some of these issues. In the long-term, the battery could support cleaner generation, specifically base load wind, improving both the overall efficiency and equity of the system.

Evaluating the net benefit or costs and determining the location of the emission increases in the NYISO system, however, requires detailed information about the dispatch order of the generators and the frequency that each plant type is on the margin in NYISO. Given the complexities of determining the dispatch order, we are unable to make an adequate estimate using public data. We recommend that the Federal Energy Regulatory Commission (FERC) task NYISO and other system operators to provide this data to allow for a comprehensive analysis of the changes in air quality and human health before siting new battery facilities.

Appendix A

To calculate the overall efficiency of integrating a battery with the NYISO system, it is necessary to know the frequency that each fuel-plant type will be used for charging the battery. This frequency is a function of the demand for electricity, the efficiency of the generator, the cost of fuel, the availability of generators (e.g. minimum run times, outages, etc…) and constraints in the transmission infrastructure. While NYISO has access to this information, it does not release these data to the public.

In this section, we describe our attempt to develop estimates of the dispatch frequencies, using an approach described in Newcomer et al. (2008) [41]. In this approach, the cost of using a given generator is estimated as the heat rate (e.g. the amount of heat required, and hence fuel, to produce a unit of electricity) multiplied by the cost of the fuel with an adder for variable maintenance and operating (VOM) as shown in Equation (A.1).

$$MC = HeatRate \cdot FC + VOM \qquad \text{... Eq. (A.1)}$$

Where MC is the marginal cost of generating electricity (in $/kWh);

HeatRate is the efficiency of the generator (in Btu/kWh);

FC is the cost of fuel (in $/Btu); and

VOM is the operating and maintenance that occurs from generating (in $/kWh).

The generators are sorted from lowest to highest MC, plotting the MC versus the available capacity for that generator. This curve is an approximation of the order that these plants would be dispatched. We then intersect this curve with the amount of electricity demanded in each hour to approximate the frequency that a plant or fuel type is used.

To construct this curve, first, we evaluate and compare three available datasets to estimate the frequency which with a given fuel-plant type is dispatched: 1) USEPA's Emissions & Generation Resource Integrated Database 2006 (eGRID2006) [13], 2) USEPA's National Electric Energy Data System (NEEDS) [42], and 3) the Ventyx Velocity Suite, a private dataset [39]. We find that none of these datasets can produce estimates of the dispatch frequencies suitable for calculating the overall efficiency as defined by Eq. (2). We conclude, however, that eGRID can be used to make preliminary estimates. Second, we show the calculations and assumptions used to construct this MC curve. Finally, we show the dispatch frequency estimates from this curve in Table A1.

A1. Comparison and evaluation of datasets

While the three datasets are based on similar data from the Energy Information Administration (EIA) [43], each of the datasets has a different amount of detail about the facilities and generators in the system and make different assumptions about generators that can operate on two different fuels (e.g. dual fuel generators that can operate on natural gas or fuel oil) and the amount of available generation. Unfortunately, differences in generator names and other features between the three datasets, however, make a direct comparison infeasible.

The eGRID dataset is compiled by the USEPA and is a comprehensive inventory of the environmental attributes of electric power plants. eGRID 2006 is based on data from 2004. It contains the heat rate for each facility. Any given facility, however, may include several units which have different heat rates and operate on different fuel types. Aggregating this heat rate and fuel types over several units could misallocate generation to either a lower or higher MC. Despite these shortcomings, Newcomer et al. (2008) used this dataset for their MC curves as it is publicly available and easy to manipulate.

The Ventyx Velocity Suite dataset is a private dataset. It has the most up-to-date information regarding the available generators in the NYISO and reflects the retirement of several large coal plants in 2007 and the addition of newer, cleaner generation. It has also disaggregated the facilities into the unit level heat rates and fuel types. This disaggregation makes this dataset more appealing for constructing the MC curve. However, this dataset is harder to manipulate as there are several build-in assumptions about the available generation capacity and it does not contain the nameplate capacity.

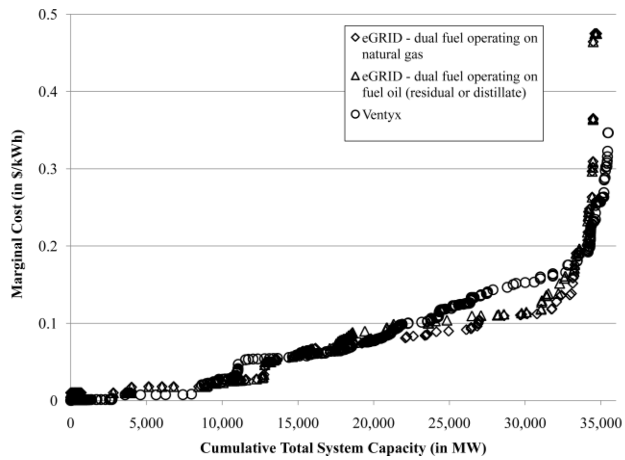
The NEEDS dataset is used to project air quality emissions for the USEPA's regulatory air quality modeling efforts (e.g. for the regulatory impact assessment of the CAIR regulations). It contains information on the heat rate and the fuel types for each unit in the system. It includes both current as well as some units which are expected to come online in the near future. While this dataset is appealing because it has information by unit, it cannot be used for this analysis since the heat rates are gross rather than net and the amount of electricity generated by fuel type is not presented.

The main problem with all these datasets is that they are static in time. In reality, the available capacity at any given generator and in the NYISO system varies by hour and by season due to maintenance, forced outages, transmission constraints and other factors. In addition, no datasets provides information on when the dual fuel capable plants are operating on which fuel. Without information on the time dependency of the available capacity and fuel usage, we cannot produce adequate estimates.

A2. Constructing the dispatch curve

To construct dispatch curves to make a rough estimate of the dispatch frequencies, we use eGRID2006 since it is publicly available. We show the curves in Figure A1. First, we calculate the MC by multiplying the heat rates with fuel prices consistent with the costs for electricity generation in New York State, obtained from the Energy Information Agency (EIA) [43, 44]. We assume that there are no net imports from outside the NYISO. Second, for each generator with a MC, we need to assign an amount of available generating capacity. The available capacity for any given generator is a function of the hour of the day and the day of the year, and this information is not available. To attempt to capture the availability of the generation, we investigate the overall availability of generation in the NYISO. We find that generation in the NYISO system has an availability of approximately 87%. Thus, we multiply the nameplate capacity of the generator by the system availability to account for forced outages, maintenance schedules and reserve margins. Whether this average captures enough of the variation in the available generation is unknown. In addition, several plants can operate on more than one fuel type. In NYISO, there are numerous turbines and boiler - steam turbine plants that can operate on NG and DFO as a result of the Minimum Oil Burn rule [19]. It is unclear, however, how to account for these plants in an average dispatch curve. With the eGRID data, we assign the entire plant to natural gas or fuel oil, and then compare the dispatch frequencies from these two curves as a bounding analysis.

Figure A1: Dispatch Curves for NYISO for eGRID and Ventyx. This curve shows the order that the electricity generators in the NYISO are dispatched as a function of cost in $/kWh. The dispatch curve for eGRID is shown with all dual fuel enabled generators operating on natural gas and all duel fuel generators operating on fuel oil.



In general, we find good agreement between the curves we constructed using eGRID and those provided by Ventyx. We observe differences due to the assumptions about the cost of fuel and the type of fuel employed, specifically at plants that can operate on more than one fuel, as well as assumptions about the amount of available capacity. One of the main differences in the curve occurs between 25,000 MW to 32,000 MW where the higher fuel prices for DFO and RFO have a significant effect on the marginal cost. Also, Ventyx calculates the cost of dispatching a generator as a weighted average of the cost for a given fuel and the fraction of the electricity produced by the fuel. We judge this approach unsatisfactory as it does not tell us which fuel is actually being used.

A3. Dispatch frequency estimates

To develop estimates of the dispatch frequencies, we intersect the eGRID curves shown in Figure A1 with actual system loads by hour for the NYISO area [45]. We show the resulting frequencies in Table A1. First, we present the frequencies if all plants that can operate dual fuel are using NG. Second, we present the frequencies if all plants that can operate on dual fuel are using fuel oil (DFO or RFO). We use these values in section 3.2 to estimate the net social value to the system of installing the battery. More information on calculating the frequency can be found in Walawalkar (2008) [46].

Table A1: Estimated frequency NYISO plant types are used for charging the battery. To obtain the frequency estimates, the dispatch curve for either all dual fuel plants operating on natural gas or on fuel oil is intersected with observed hourly loads in the NYISO. Summing the number of hours that the load intersects a given fuel type and dividing by the number of hours a year yields the following frequencies.

Fuel Type	Dual Fuel Plants Operating as Natural Gas	Dual Fuel Plants Operating as Fuel Oil
Coal plant	1.3%	1.3 %
Natural gas plant	97.4 %	42.6%
Fuel oil (residual or distillate)	-	52.6%
Other	1.3%	3.5 %

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Supplementary Material

Figure S1: Average change in concentrations of O_3 in ppb for an uncontrolled coal plant

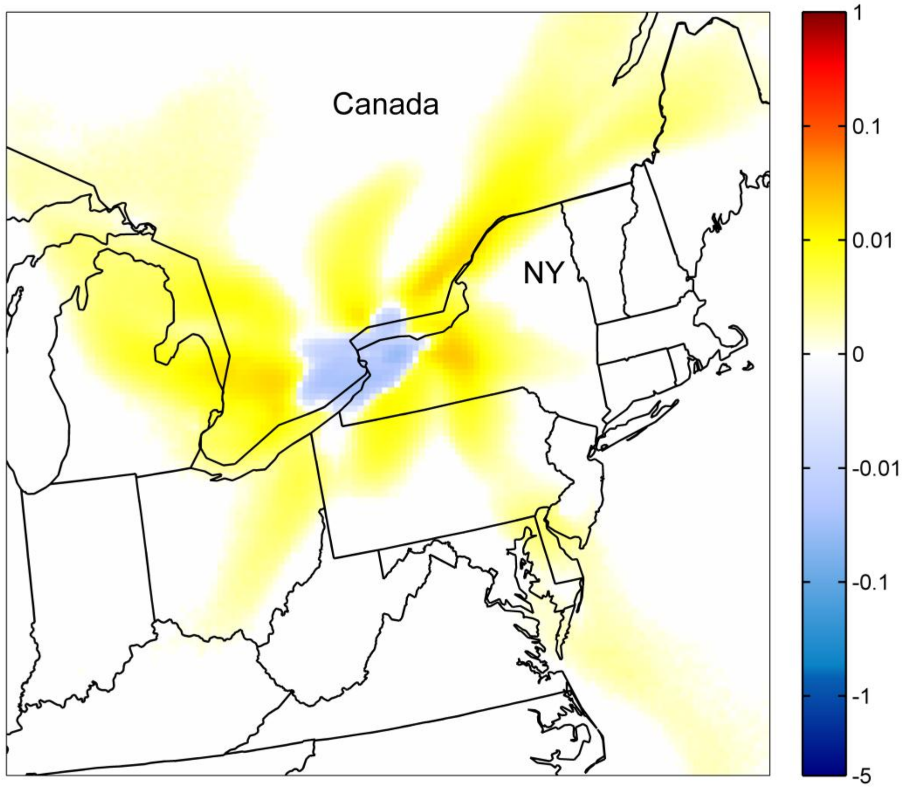

Figure S2: Average change in concentrations of O_3 in ppb for a residual fuel oil boiler-steam turbine plant

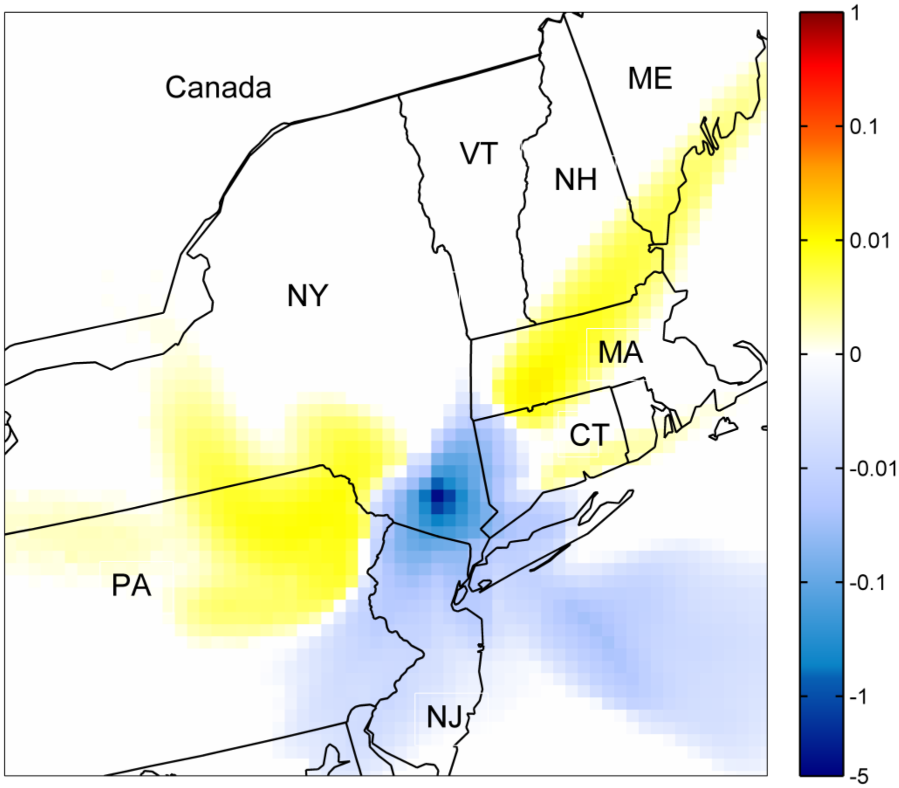

Table S1: Social costs for charge-displace plant combinations in ¢/kWh with 5% and 95% confidence intervals for changes in $PM_{2.5}$ and O_3. Positive values represent a social cost and negative values represent a social benefit.

Charging Plant \ Displaced Plant	**DFO turbine**	**NG turbine**
Uncontrolled coal	$PM_{2.5}$: 16.5 (4.14 – 35.3) O_3: 10.2 (2.36 – 19.1)	$PM_{2.5}$: 28.6 (7.17 – 61.1) O_3: 8.20 (1.89 –15.3)
Controlled coal	$PM_{2.5}$: -12.6 (-26.9 – -3.15) O_3: 12.7 (2.93 – 23.7)	$PM_{2.5}$: -0.52 (-1.11 – -0.13) O_3: 10.2 (2.36 – 19.1)
IGCC coal	$PM_{2.5}$: -15.0 (-32.0 - -3.75) O_3: 13.0 (3.00 – 24.3)	$PM_{2.5}$: -2.90 (-6.21 – -0.73) O_3: 10.4 (2.41 – 19.1)
RFO boiler	$PM_{2.5}$: -8.00 (-17.1 – -2.00) O_3: 6.55 (1.51 – 12.2)	$PM_{2.5}$: 4.06 (1.02 – 8.68) O_3: 7.66 (1.77 – 14.3)
NG boiler	$PM_{2.5}$: -14.3 (-30.5 – - 3.58) O_3: 7.65 (1.77 – 18.2)	$PM_{2.5}$: -2.22 (-4.74 – -0.55) O_3: 8.95 (2.07 – 21.9)
NG combined cycle	$PM_{2.5}$: -15.1 (-32.4 – -4.15) O_3: 9.74 (2.25 – 18.2)	$PM_{2.5}$: -3.08 (-6.58 – -0.77) O_3: 11.4 (2.63 – 21.3)
Wind	$PM_{2.5}$: -16.6 (-35.4 – -4.15) O_3: 13.7 (3.17 – 25.6)	$PM_{2.5}$: -4.49 (-9.60 – -1.13) O_3: 11.7 (2.70 – 21.9)
RFO boiler – New York	$PM_{2.5}$: 1.88 (0.47 – 4.01) O_3: 7.51 (1.74 – 14.0)	$PM_{2.5}$: 16.8 (4.21 – 35.9) O_3: 5.51 (1.27 – 10.3)
NG boiler – New York	$PM_{2.5}$: -13.4 (-28.5 – -3.34) O_3: 6.43 (1.48 – 12.0)	$PM_{2.5}$: 1.59 (0.40 – 3.39) O_3: 4.71 (1.10 – 8.81)

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