Emissions Impacts of Wind and Energy Storage in a Market Environment

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Abstract

This study examines the emissions impacts of adding wind and energy storage to a market-based electric power system. Using Texas as a case study, we demonstrate that market power can greatly effect the emissions benefits of wind, due to most of the coal-fired generation being owned by the two dominant firms. Wind tends to have less emissions benefits when generators exercise market power, since coal-fired generation is withheld from the market and wind displaces natural gas-fired generators. We also show that storage can have greater negative emissions impacts in the presence of wind than if only storage is added to the system. This is due to wind increasing on- and off-peak electricity price differences, which increases the amount that storage and coal-fired generation are used. We demonstrate that this effect is exacerbated by market power.

Introduction

Recent years have seen increased interest in renewable electricity in the U.S. and elsewhere. This interest has been driven by several factors, one of which is the emissions and environmental impact of conventional fossil-fueled generation. Wind has provided the bulk of renewable capacity

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expansion, due to its currently being the lowest-cost technology and the abundance of wind resources. Energy storage is often discussed as an enabling technology that can ease the integration and improve the economic and technical characteristics of wind (*1–13*).

Denholm *et al*. (*14*) examine the emissions of a wind generator that uses storage to provide baseload energy. They show that life cycle greenhouse gas emissions from such a baseload wind system can be less than 20% of a combined-cycle natural gas-fired generator. Denny and O'Malley (*15*) estimate the emissions impacts of wind and storage in the Irish system. Their analysis is based on a perfectly-competitive model, in which the operation of conventional generation is co-optimized with wind and storage to minimize system costs. They focus on the impact of wind uncertainty and part-load operation of conventional generators on system emissions. Their results show that wind will have much greater effects in reducing CO_2 emissions as compared to SO_2 and NO_x.

One limitation of these analyses is that they neglect interactions between wind, storage, and the market. Since wind participates in wholesale electricity markets (*16*), a wind generator may prefer using storage to maximize energy revenues as opposed to providing baseload energy. Indeed, storage analyses assume such operations to maximize revenues from charging and discharging energy, an activity referred to as energy arbitrage (*17–21*). Adding wind and storage to a system together can increase this use of storage, since wind tends to suppress energy prices (*22–24*). This price suppression is due to wind displacing higher-cost generation. Another factor that can influence the emissions impacts of wind and storage is the competitiveness of the generation sector. Generating firms exercise market power by withholding capacity from the market (*25*, *26*). Thus depending on the ownership of generation and the extent to which different firms have market power, the actual mix of generators used and the type of generation that wind or storage displace can vary.

This study examines the emissions effects of wind and storage when accounting for market price effects on storage use. We consider two cases, one with a perfectly-competitive generation sector and another in which the two dominant firms exercise market power. We use an optimization model to represent the interactions between conventional generators, wind, and storage, which is used to derive the dispatch of the system over a one-year period (*24*). The optimized dispatch is combined with emissions rates estimates to model generator emissions of CO_2, SO_2, and NO_x with and without wind and storage.

Methods

Our analysis is based on the Electricity Reliability Council of Texas (ERCOT) system in 2005. ERCOT had about 2 GW of wind installed in 2005, which are included in the base system. We compare the base system to systems with up to 10 GW of added wind and up to 10 GW of storage with up to 20 hours of charging capacity. For purposes of comparison, ERCOT had about 83 GW of generation capacity installed and a peak load of 60 GW in 2005.

Ownership and Market Structure

ERCOT had about 81 GW of conventional (*e.g.* thermal and hydroelectric) generation installed in 2005, of which about 16 GW were coal-fired, 60 GW natural gas-fired, and the remaining used other fuels (*27*). These assets were divided between 53 firms. Of these, two firms—Luminant and Texas Genco—owned a large share of about 18% and 14% (on a capacity basis), respectively. Between them, these two firms owned about 65% of the coal-fired capacity in the system.

Analyses of the ERCOT market suggest that Luminant and Texas Genco have historically had a greater tendency to exercise market power than the other firms (*28*, *29*). Thus we model wind and storage impacts under two market competitiveness cases: the first, which we refer to as the competitive case, assumes that all 53 generating firms behave perfectly competitively; the other, referred to as the oligopoly case, assumes that Luminant and Texas Genco behave as profit-maximizers while the remaining 51 firms behave competitively. Further details regarding the breakdown of generation ownership and the market competitiveness cases considered are given in the Supporting Information.

Market Operation

In both the competitive and oligopoly cases, we assume that the generating firms submit supply functions, $q_{i,t}(p)$, to a market operator. The function $q_{i,t}(p)$ specifies the maximum amount of energy that firm i is willing to supply in hour t as a function of price. In the competitive case, the supply functions are the inverse of the firms' marginal cost functions. In the oligopoly case, Luminant and Texas Genco's supply functions are found by solving a profit-maximization problem, while the remaining firms submit supply functions equal to the inverse of their marginal cost functions. The derivation of these supply functions do not take into account dynamics of conventional generators, such as ramping limits, minimum load constraints, and startup costs. Each firm's cost function is estimated based on the heat rates of the generators that it owns and fuel prices. Heat rate and fuel price data are obtained from Global Energy Decisions and Platts Energy. We use stepped heat rate functions, which capture differences in a generator's efficiency as a function of its output.

Modeling Wind and Storage

Letting D_t be the system load and X_t net energy sales from wind and storage (*30*) in hour t, the market operator sets the hour-t price of energy as:

$$p_t^*(X_t) = \min_p \left\{ p \,\middle|\, \sum_{i=1}^{N} q_{i,t}(p) = D_t - X_t \right\}, \tag{1}$$

where N is the number of generating firms. Eq. (1) defines the price such that it induces exactly enough supply from the conventional generating firms to serve the load net of wind and storage sales.

The profit of wind and storage over a T-hour time horizon is given by:

$$\sum_{t=1}^{T} p_t^*(X_t) \cdot X_t. \tag{2}$$

We model the behavior of wind and storage by maximizing this profit, subject to technical constraints on the storage plant and the availability of wind energy. Thus even in the competitive generation case, we assume the wind and storage choose their net sales to maximize profits. This allows us to capture the emissions impacts of competitiveness of the generation sector, without differences in the assumed behavior of wind and storage confounding the results. Storage constraints include roundtrip efficiency losses of the storage system, which we assume to have an 80% roundtrip efficiency, and power and energy capacity limits (*20, 24*). This profit-maximization model does not impose any restrictions that only energy from wind be stored. Thus net wind and storage sales could be negative, which would imply that energy is purchased from the market and stored. Further details of this profit-maximization model are given in the Supporting Information.

Estimating Emissions

We model emissions associated with the combustion of fossil fuels in generators only. We therefore assume that there are no emissions directly associated with storage use or wind generation. The amount of energy that generating firm i must supply in hour t is given by $q_{i,t}\left(p_t^*(X_t)\right)$. Generator emissions are estimated based on these hourly generation levels using input-based emissions rates, which give kg of each pollutant released per GJ of fuel burned. This is in contrast to output-based emissions rates, which give kg of each pollutant released per MWh of electricity generated. Using input-based emissions rates better accounts for differences in generator heat rates caused by operating a generator at part-load.

CO_2 emissions rates are assumed to be constant for each generator. To account for the impact of part-load operations on the effectiveness of emissions controls, we assume that the SO_2 and NO_x emissions rates of each generator can vary as a function of generating load. We approximate these emissions rates using a Nadaraya-Watson kernel estimator (*31–33*). We use separate kernel estimates for NO_x emissions rates during an ozone season, which is from May to September, and a non-ozone season, which covers the remaining months. This assumption reflects the possibility of more stringent NO_x restrictions being in place during the ozone season, since NO_x is an ozone precursor. Such restrictions may result in greater use of emissions controls. The emissions rates are estimated using continuous emissions monitoring system (CEMS) data for the year 2005 obtained from the U.S. Environmental Protection Agency. The CEMS data record GJ of fuel burned and kg of CO_2, SO_2, and NO_x released by each generator on an hourly basis.

Wind Data

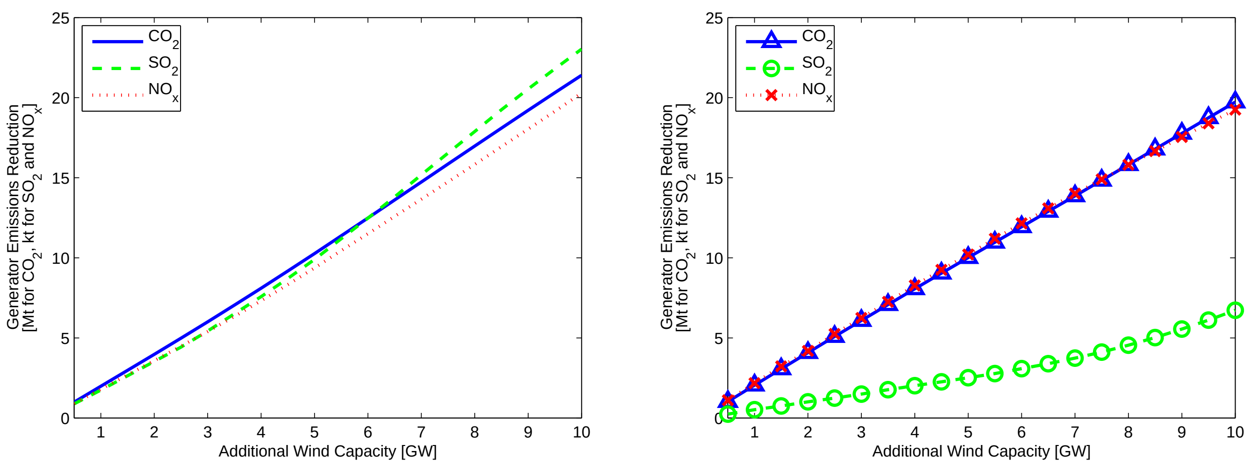
We use modeled wind generation data developed by 3TIER for the National Renewable Energy Laboratory's Western Wind and Solar Integration Study (WWSIS) to model wind generation. This dataset provides wind data for 2005 at sites across Texas. We model the 2 GW of wind capacity that were installed in Texas in 2005 by associating each actual wind generator to a location in the WWSIS dataset, based on geographic distance. We assume that the additional wind generators that we model are located at the same sites as actual wind generators that were or are planned to be installed between 2005 and 2011. We use the location of these planned installations to associate the incremental wind capacity with locations in the WWSIS dataset.

Results

Emissions Impacts of Wind

Coal is a less costly generation fuel than natural gas. Thus in the competitive case, wherein all of the generators submit cost-based supply functions to the market, coal is used as baseload generation and natural gas is used for any additional load above the capacity of coal-fired plants. The system is not dispatched on the basis of cost in the oligopoly case, however, because the two dominant firms submit supply functions that are above their marginal costs. These above-cost supply functions act to withhold some of the dominant firms' generating capacity from the market, forcing the market operator to use higher-cost generation which increases energy prices and firm profits. Because the dominant firms own much of the coal-fired generation, this withholding causes differences in the breakdown of the generation load. In the base system, coal constitutes about 46.1% of fossil-fueled generation in the competitive case as opposed to 45.8% in an oligopoly. The withholding of coal-fired generation occurs during low-load periods, in which the dominant firms' natural gas-fired generators are shutdown. By submitting above-cost bids for their coal-fired generators, the dominant firms force the market operator to use more (of the dominant or competitive firms') natural gas-fired generation, increasing the price of energy. This greater use of coal gives higher emissions in the competitive case due to the higher emissions rates of coal—CO_2, SO_2, and NO_x emissions are 235 Mt, 461 kt, and 202 kt, respectively, in the competitive case as opposed to 230 Mt, 448 kt, and 171 kt in an oligopoly.

These differences in the dispatch also affect the emissions reductions when wind is added to the system. Figure 1 shows annual emissions reductions when wind is added to the base system. The figure shows that CO_2 and NO_x reductions are roughly linear in the amount of wind added to the system and that the emissions reductions are comparable between the competitive and oligopoly cases. Marginal SO_2 reductions are, on the other hand, increasing in the amount of wind added to the system. Wind also has a greater impact in reducing SO_2 emissions in the competitive case.



(a) Competitive case.

(b) Oligopoly case.

Figure 1: Total annual reduction in generator emissions of CO_2, SO_2, and NO_x when wind is added to the system. CO_2 reductions are reported in Mt, and SO_2 and NO_x reduction are reported in kt. Figure 1a shows emissions reductions in the competitive case and Figure 1b shows emissions reductions in the oligopoly case.

The differences in SO_2 reductions are due to the impact of wind on natural gas- as opposed to coal-fired generation. Because of capacity withholding in an oligopoly, there are fewer hours, compared to the competitive case, in which coal-fired generation is marginal and displaced by wind. Thus, the first 5.5 GW of wind added to the system have a relatively modest effect with an average of 111 MWh of coal-fired generation being displaced annually per MW of added wind capacity. The same 5.5 GW of wind have a much greater impact in the competitive case, with 896 MWh of coal-fired generation being displaced on average per MW of wind. Additional wind beyond the first 5.5 GW have a greater impact, however, since at sufficiently high penetrations coal-fired generation will increasingly be marginal and displaced. Each additional MW of wind beyond the first 5.5 GW results in annual coal-fired generation reductions of between 145 MWh and 389 MWh in the oligopoly case. This incremental wind has an even greater impact in the competitive case, however, with annual coal-fired generation reductions of between 1,097 MWh and 1,208 MWh per MW of added wind.

Emissions Impacts of Storage

Figure 2 shows annual emissions increases when storage with four hours of charging capacity is added to the system and used for arbitrage. The trends are similar for different numbers of charging hours. In all of the cases CO_2 and SO_2 emissions increase when storage is added, whereas NO_x emissions decrease in some cases. The emissions increases are due to two effects. One is that more energy must be generated, due to roundtrip efficiency losses of storage. The other is that storage is used to arbitrage price differences between on- and off-peak hours. In the competitive case, much of this arbitraging is done between coal and natural gas-fired generation. Coal-fired generators provide between 38% and 50% of the incremental generation when energy is charged into storage, whereas more than 98% of the generation displaced when storage is discharged is natural gas-fired. Due to the exercise of market power, coal-fired generation provides less than 5% of the energy stored in the oligopoly case. In this case, storage is largely arbitraging price differences between more-efficient combined-cycle and less-efficient simple-cycle natural gas plants. This difference in the generation used to provide the charging energy explains the significantly higher SO_2 increases in the competitive case.

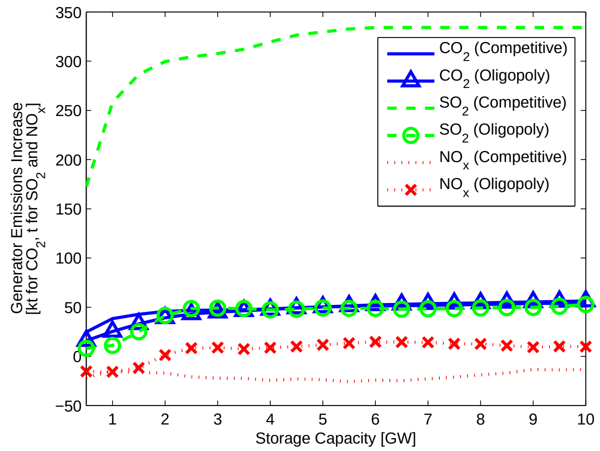


Figure 2: Total annual increase in generator emissions of CO_2, SO_2, and NO_x when energy storage with four hours of charging capacity is added to the base system with no additional wind. CO_2 increases are reported in kt, and SO_2 and NO_x increases are reported in t.

These findings of increased emissions and the sensitivity to the generating fuels used and displaced when storage is charged and discharged are consistent with other storage analyses. Denholm and Holloway (*34*) examine the emissions impact of compressed-air energy storage (CAES) in Ohio. They show that since CAES could be charged using coal-fired generation and displace natural gas-fired generation when discharged, the net emissions of CAES could be greater than a new coal-fired generator. They also show that CAES could have significantly lower emissions if storage is charged using cleaner generation, such as nuclear, renewable, or new coal that meets 2004 Clean Air Act standards.

Figure 2 also shows that emissions will not necessarily be monotone in the power capacity of the storage plant. This is because storage will affect the output of marginal generators, which can change their emissions rates. For instance, there is an approximately 1 t reduction in SO2 emissions in the oligopoly case between 5 GW and 5.5 GW of storage. This difference is due to a 5.5 GW storage plant doing more arbitrage than a 5 GW plant on 30 August. This increased arbitraging results in two of the coal-fired plants shifting their generation between hours with different emissions rates. This type of emissions fluctuation is likely specific to the 2005 data used in our case study, and should not be interpreted as a general result that will occur in all years. Storage has similar effects on NO_x and decreases NO_x emissions in some cases. This is because the shifting of generating loads results in marginal generators having lower emissions rates. These lower rates yield a NO_x reduction, which outweighs the emissions increase caused by greater generation and the arbitraging effect.

Joint Emissions Impacts of Wind and Storage

Adding wind and storage to a system together increases storage use compared to the storage-only case. This is because wind suppresses energy prices by displacing high-cost generation from the market. Since this price effect is associated with wind availability and hourly wind availability can be highly variable, wind increases hourly price differences and arbitrage opportunities. Our analysis assumes joint ownership of wind and storage, however the same effects persist in a disjoint-ownership case and storage use and emissions impacts will largely be the same in the two cases. This is because wind will have the same price-suppressing impact regardless of storage ownership.

Figure 3 shows, as an example, the operation of 5 GW of storage with four hours of charging capacity on a sample day in a system with 10 GW of added wind. It shows hourly wind generation and total net sales from wind and storage when storage use is optimized to maximize energy revenues. Comparing the hourly wind output and net sales profiles shows that storage is used extensively on this day. About 11 GWh of energy are stored in the morning and afternoon when wind suppresses energy prices. This energy is later discharged in the late morning and evening when wind generation is lower and prices are higher. The figure also shows the breakdown of the change in hourly conventional generation caused by storage. This is shown as the change in natural gas-fired generation between the wind-only and wind-and-storage cases, as a percentage of the change in total conventional generation between these two cases. Coal-fired generation provides roughly a third of the incremental energy when storage is charged on this day in the competitive case, as opposed to only 13% in an oligopoly. There are also differences in the generation that is displaced when storage is discharged—roughly 88% of the displaced generation is natural gas-fired in the competitive case as opposed to 99% in an oligopoly.

These types of differences persist throughout the year and with different wind and storage

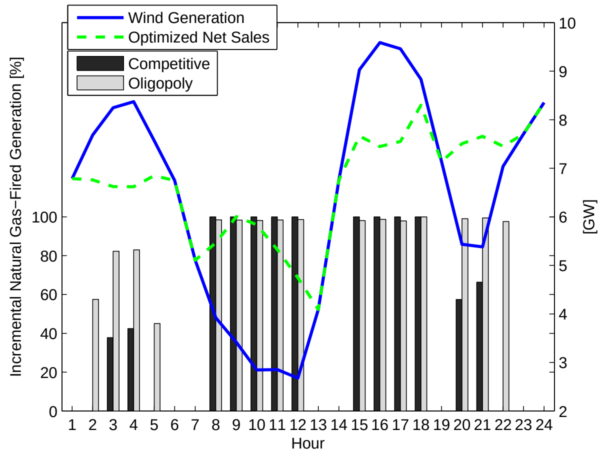
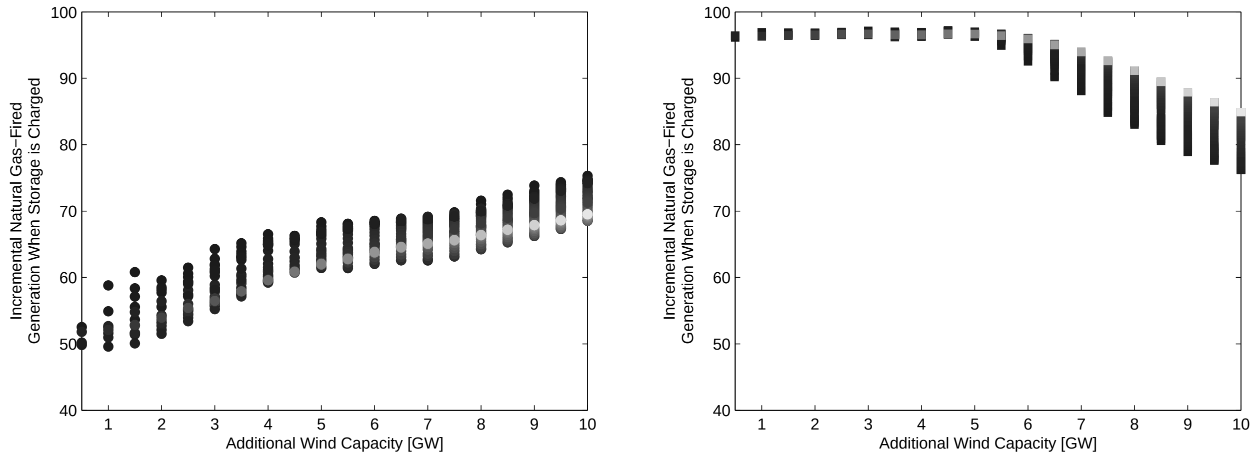


Figure 3: Hourly output of a 10 GW wind plant, net sales from a 5 GW storage plant with four hours of charging capacity, and resulting changes in conventional generation on 15 January. Storage use is assumed to be co-optimized with wind to maximize total profit. Bars show the change in total natural gas-fired generation between the wind-only and wind-and-storage cases, as a percentage of the change in total conventional generation between the two cases.

penetrations. Figure 4 shows the marginal effect of charging storage on conventional generation. The figure shows the change in natural gas-fired generation between wind-only and wind-and-storage cases during hours of the year in which storage is charged, as a percentage of the total change in conventional generation during those hours. The shading of the circles and squares is based on the energy capacity of the added storage—lighter shading indicates more storage. The figure shows that coal-fired generation tends to provide more of the incremental generation when storage is charged in the competitive case, due to it being marginal in more hours. The differences in the composition of the charging load between the competitive and oligopoly cases decreases as more wind is added, however. This is because adding more wind in the oligopoly case will increasingly displace coal-fired generation, making coal the marginal generating fuel in more low-price hours. There are also small differences in the breakdown of the conventional generation that is displaced when storage is discharged. Between 84% and 99% of the generation displaced when storage is discharged is natural gas-fired in the competitive case, whereas this number is always above 97% in an oligopoly.

Figure 5 shows the effect of these differences in incremental generation when storage is charged and discharged on the net emissions impact of adding storage and wind to a system together. The



(a) Competitive case.

(b) Oligopoly case.

Figure 4: Incremental natural gas-fired generation when storage is charged, as a percentage of change in total conventional generation when storage is charged. Generation changes shown are between wind-only and wind-and-storage cases. The shading of the circles and squares are based on the energy capacity of the added storage—lighter shading indicates more storage. Figure 4a shows generation changes in the competitive case and Figure 4b shows generation changes in the oligopoly case.

figure shows emissions increases between a case with 10 GW of added wind only and a case with 10 GW of wind and storage with four hours of charging capacity. With the exception of NO_x in the oligopoly case, the combination of wind and storage causes all emissions to increase. The figure shows that the emissions impacts of wind and storage together are highly sensitive to amount of wind and storage added. For instance, there are greater SO_2 increases in the competitive as opposed to oligopoly case if less than 8 GW of storage is added, whereas these impacts are reversed for larger amounts of storage. This is because in an oligopoly with less than 5 GW of storage, coal-fired generation provides about 21% of the incremental energy when storage is charged. As storage capacity increases, coal's share of charging energy drops to below 16%. In the competitive case, however, coal always provides between 25% and 29% of the added load when storage is charged. Thus as more storage is added to the system, storage is decreasingly arbitraging between coal- and natural gas-fired generation in an oligopoly, reducing its SO_2 impact relative to the competitive case.

Comparing the range of emissions increases in Figure 2 and Figure 5 shows that the emissions

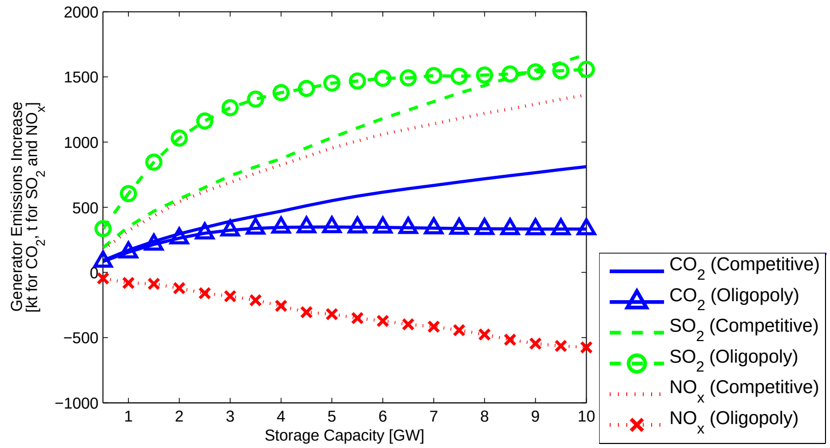


Figure 5: Total annual increase in generator emissions of CO_2, SO_2, and NO_x when energy storage with four hours of charging capacity is added to a system with 10 GW of added wind. Emissions increases are relative to the wind-only case. CO_2 increases are reported in kt, and SO_2 and NO_x increases are reported in t.

impacts of storage in a system with wind are, in some cases, two orders of magnitude greater compared to if there is no added wind. This is because wind significantly increases arbitrage opportunities for storage. For instance, 5 GW of storage with four hours of charging capacity stores about 321 GWh and 529 GWh of energy in the competitive and oligopoly cases, respectively, if no wind is added to the system. The same storage plant stores about 3.4 TWh and 3.6 TWh of energy in the competitive and oligopoly cases, respectively, if 10 GW of wind is also added to the system. Thus the combination of wind and storage yields superadditive emissions impacts relative to the impacts of introducing the two technologies to the system individually.

We can measure this superadditive effect by defining:

$$M_{u,a}, \tag{3}$$

as the annual emissions of pollutant u under deployment scenario a, where a denotes either the base ($a = B$), storage-only ($a = S$), wind-only ($a = W$), or wind-and-storage ($a = WS$) case. We can then measure the superadditive effect of adding wind and storage together as:

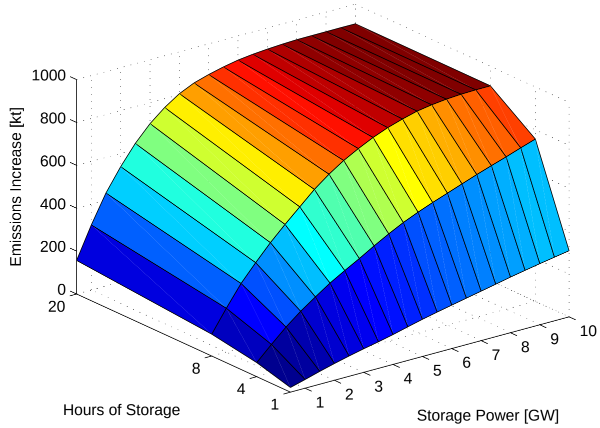
$$\xi_u = (M_{u,WS} - M_{u,W}) - (M_{u,S} - M_{u,B}), \tag{4}$$

which is the emissions increase between the wind-and-storage and wind-only cases, less the emissions increase between storage-only and base cases. Thus ξ_u measures the extent to which storage impacts generator emissions due to the increased arbitrage opportunities created by wind. Figure 6 summarizes the values of ξ_u with different amounts of storage and 10 GW of wind. The increases in the competitive case are relatively small compared to the emissions benefits of wind, representing up to 8% of the emissions savings from introducing wind to the system. The combination of wind and storage have much more pronounced effects in the oligopoly case, however. The SO_2 increases represent up to 24% of the SO_2 reductions from wind, thus the combination of wind and storage can eliminate close to a quarter of the SO_2 savings from wind. On the other hand, wind and storage together reduce NO_x emissions compared to the wind-only case. This is because the changes in conventional generator loads improves the NO_x emissions rates of marginal generators, yielding a net NO_x reduction that outweighs increased emissions due to higher generating loads.

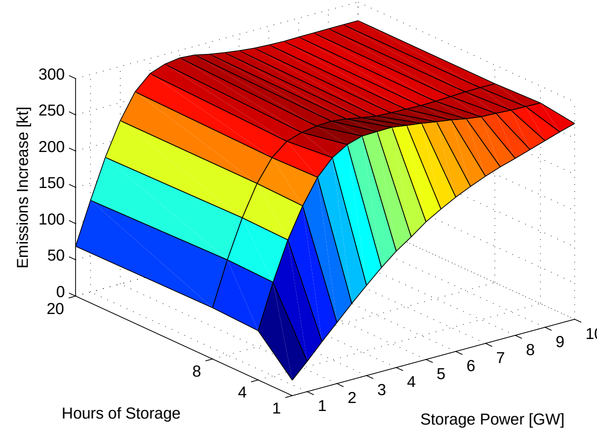
Discussion

Although storage is discussed as a technology to improve the characteristics of wind, these results show that storage and wind can interact in ways that increase the emissions impact of storage. Conventional generator ownership, market competitiveness, and the penetration of wind and storage can substantively change the emissions impacts of these technologies individually and together. Our analysis assumes up to 10 GW of wind is added to a base system with 2 GW of wind. ERCOT has close to 10 GW of wind installed today, thus the impacts of an additional 10 GW on top of this would be different than our estimates. For example, it is likely that wind would have a greater impact on SO_2 emissions, since the relatively high wind penetrations would result in coal-fired generation being marginal in significantly more hours.

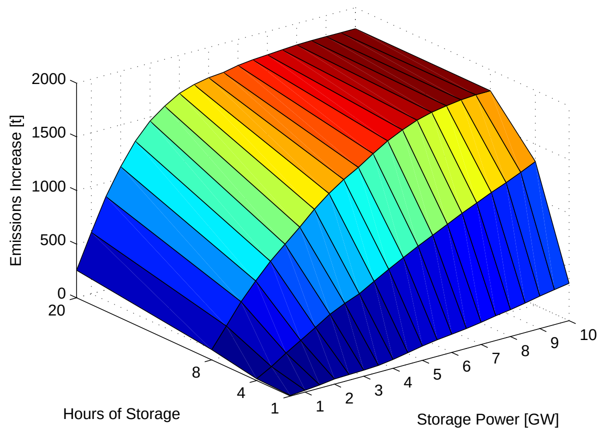
Although our case study is based on the ERCOT system, our results should be viewed as illustrative. This is because the ERCOT market is not perfectly competitive, nor do the two dominant firms fully behave as profit-maximizers. Thus the competitive and oligopoly cases should be



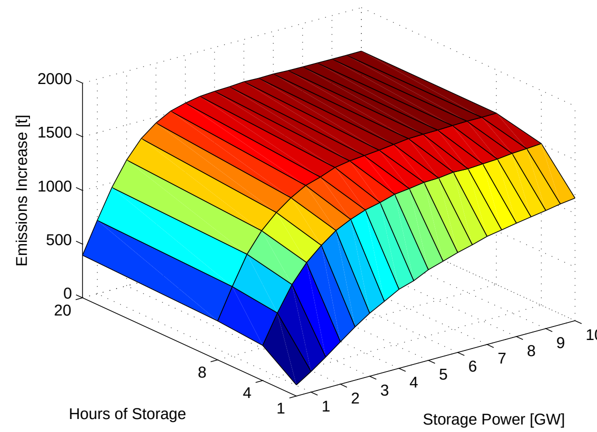
(a) Competitive case CO_2.



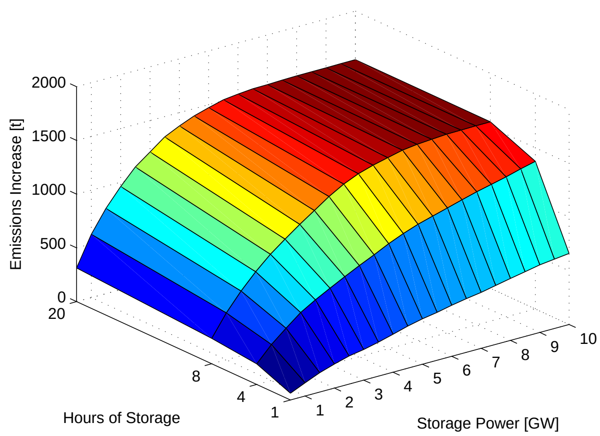
(b) Oligopoly case CO_2.



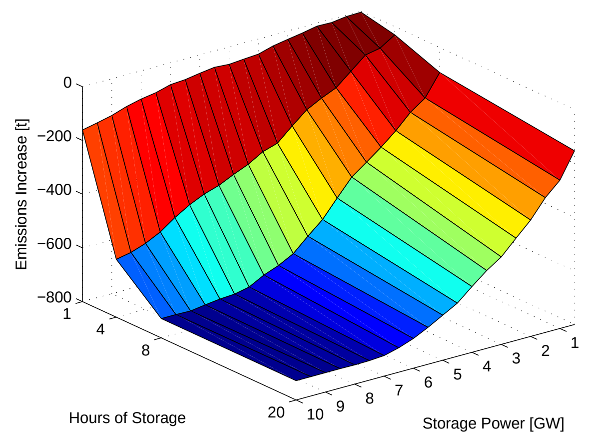
(c) Competitive case SO_2.



(d) Oligopoly case SO_2.



(e) Competitive case NO_x.



(f) Oligopoly case NO_x.

Figure 6: Total annual increase in generator emissions of CO_2, SO_2, and NO_x when storage is added to a system with 10 GW of wind. The figures show the increase between wind-and-storage and wind-only cases, less the emissions increases between storage-only and base cases. CO_2 increases are reported in kt and SO_2 and NO_x increases are reported in t.

viewed as providing bounds on the impacts of wind and storage. Some of the emissions fluctuations (*e.g.* non-smooth and non-monotone emissions impacts of wind and storage) are possibly specific to the 2005 data that we base our analysis on, and may not be general results. Nevertheless, the findings regarding shifting of generation between generating fuels and technologies would likely occur in other systems. This is because marginal generating technologies and emissions rates can differ by time of day and also be sensitive to market competitiveness. For instance, California has virtually no coal-fired generation. Nevertheless, hourly marginal emissions rates can vary depending on whether combined- or simple-cycle natural gas-fired generation is marginal (*35*).

Our analysis assumes joint ownership of wind and storage, because storage is considerably more valuable to a wind generator than to a standalone storage operator or conventional generator (*24*, *36*). As noted before, storage use and emissions impacts would largely be the same with disjoint ownership of wind and storage. Our joint-ownership assumption should not, however, be taken to suggest that wind and storage must or should be jointly owned. Our analysis further assumes that wind and storage are owned by a single profit-maximizing firm. Although wind ownership was rather concentrated in 2005 (Table S3 in the Supporting Information summarizes wind ownership), this assumption may overstate the extent to which wind and storage can exercise market power by adjusting net sales to maximize profits. Relaxing this assumption would not affect wind generation, since wind is never curtailed in our model. Storage use could increase, however, since it is profit-maximizing to reduce storage use from a competitive level to maintain higher price differences between on- and off-peak periods (*20*, *36*). Based on our findings, it is likely that this greater use of storage would yield higher generator emissions.

Our model does not consider operational impacts that wind and storage can have on power systems. Storage can provide valuable renewable integration services, such as reducing the need for transmission expansions and wind curtailment (*13*, *37*). These types of interactions between wind and the power system arise due to dynamics of conventional generators, such as ramping limits, minimum load constraints, and startup costs, that cannot be accommodated in the model that we use. Some of these services can decrease system emissions. For example, wind generation variability can require inefficient fast-ramping generators, that often have high emissions rates, to follow wind supply (*38*). If storage can reduce the variability of wind, this can reduce the need for such generation and the associated emissions. Storage can also increase the profitability of a wind generator, which could spur or encourage further wind capacity to enter the market (*24*). Since these types of benefits are not directly captured in our model, such gains should be weighed against the impacts that we estimate here.

Acknowledgement

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Supporting Information Available

A summary overview of the ERCOT market structure and more detailed description of our market and storage modeling methodology and assumptions. This material is available free of charge via the Internet at `http://pubs.acs.org/`.

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Supporting Information

Emissions Impacts of Wind and Energy Storage in a Market Environment

Ramteen Sioshansi

8 Pages with 3 Tables

ERCOT Market Structure

Generation assets in the ERCOT market were divided between 53 firms, ranging from large investor-owned utilities to small industrial cogenerators, in 2005. Table S1 shows the breakdown of the assets among the seven largest generating firms, based on installed generating capacity, as reported in form 860 data collected by the U.S. Department of Energy's Energy Information Administration. The remaining 46 firms each own less than 5% of the generating capacity in the system.

Table S1: Breakdown of generation assets, on a capacity basis, among seven largest generating firms in 2005. The remaining 46 firms each own less than 5% of the generation capacity in the market.

Generating Firm	Generating Capacity (%)
Luminant	18
Texas Genco	14
Coral Energy	7
CPS Energy	7
Exelon Generation	6
Calpine	6
Austin Energy	6

Analyses of the ERCOT market suggest that the two largest firms, Luminant and Texas Genco, tend to exercise market power whereas the remaining firms behave more competitively (*28*, *29*). These analyses compare actual historical bids that the firms submit into the balancing energy market to models of profit-maximizing behavior. Both analyses find that Luminant and Texas Genco's bidding behavior in the market is closest to profit-maximizing, insomuch as they tend to submit bids above cost and they earn profits that are near-optimal. Nevertheless, they find that the behavior of these firms is not exactly profit-maximizing. They posit that the threat of regulatory intervention and market mitigation places some pressure on them to constrain their bids. The remaining firms, by contrast, tend to submit highly price-inelastic supply functions compared to the profit-maximizing benchmark. Both analyses conclude that the amount of revenue that these smaller firms could earn from profit-maximizing bidding is too small to warrant the associated costs. Instead, these firms likely competitively contract to sell their energy on a bilateral basis.

For these reasons, we consider two market competitiveness cases. The first assumes that all firms behave competitively and submit cost-based bids. The second assumes that only the two largest firms exercise market power by submitting profit-maximizing bids into the market, while the remaining firms submit competitive cost-based bids. Given the empirical findings regarding market behavior, these are likely bounding cases, with the true impacts of wind and storage being closer to the oligopoly case. Table S2 summarizes the breakdown of generation technologies in the ERCOT market in 2005 between the dominant firms and the competitive fringe, on a capacity basis.

Table S2: Breakdown of thermal generation technologies between dominant firms and competitive fringe, on a capacity basis, in 2005.

Generating Fuel	Dominant Firms	Competitive Fringe
Nuclear	71	29
Coal	65	35
Natural Gas Combined Cycle	4	96
Natural Gas Steam Turbine	37	63
Natural Gas Combustion Turbine	55	45

Modeling Wind, Storage, and Generator Behavior

We model the interaction between the wind generator, storage plant, and the conventional generators as a Stackelberg-type equilibrium, in which the wind generator and storage plant are leaders and the conventional generators are followers. We assume this sequential strategic interaction, as it allows us to use an SFE to model conventional generator behavior in the oligopoly case (*24*). The wind generator and storage plant are assumed to make decisions about how many MWh of energy to sell in each hour, and the conventional generators then compete by submitting bids to the market. We assume that the market participants all follow a subgame-perfect Nash equilibrium, and as such we first analyze the behavior of the conventional generators.

Conventional Generator Behavior

In both the competitive and oligopoly cases we assume that the conventional generators submit supply functions of the form $q_{i,t}(p)$ to the market. This function specifies how much energy firm i is willing to generate in hour t as a function of the price, p. In the competitive case, firms submit supply functions equal to the inverse of their marginal cost functions. We compute costs based on the portfolio of generators that each firm owns, generator heat rates reported by Global Energy Decisions, and energy prices reported by Global Energy Decisions and Platts Energy.

In the oligopoly case, we model the behavior of the two largest firms using the SFE model (*39*). The SFE model is widely used in modeling conventional electricity markets (*40–44*) and electricity markets with renewables (*22*). This is because the SFE model assumes that firms compete by submitting supply functions into a spot market, which is quite reminiscent of how actual electricity markets operate. Most electricity markets have firms submit price/quantity pairs, which can be viewed as a discretized supply function (*40*).

To derive the SFE, we define $c_{i,t}(q_{i,t})$ as firm i's cost in hour t as a function of the amount of energy, $q_{i,t}$, that it generates in hour t. Let $D_t(p) + \varepsilon_t$ denote the system load in hour t, where $D_t(p)$ is a price-elastic demand function and ε_t is a random demand shock. Because we assume that all of the firms except the two largest submit competitive supply functions, we define $D_t(p)$ as the difference between the actual historical system demand and the supply functions of the competitive firms. The SFE model assumes the random shock to ensure a non-degenerate solution (*39*). In the context of an electricity market, such uncertainty exists because system loads cannot be perfectly predicted when bids are submitted to the market (*28*). Finally, let X_t denote net sales from wind and storage in hour t, which the conventional generators are assumed to know due to the sequential nature of the market interaction.

Firm i determines its optimal hour-t supply function by solving the following profit-maximization problem:

$$\max_{p} \Pi_{i,t}(p) = p \cdot \left[D_t(p) - X_t + \varepsilon_t - \sum_{j \in \omega(i)} s_{j,t}(p) \right] - c_i \left(D_t(p) - X_t + \varepsilon_t - \sum_{j \in \omega(i)} s_{j,t}(p) \right), \quad \text{(S1)}$$

where $\omega(i)$ denotes the set of profit-maximizing generating firms in the market other than firm i. The first-order necessary condition for each firm's optimal choice of p can be manipulated to yield the following set of coupled differential equations (there will be one equation for each profit-maximizing firm):

$$q_{i,t}(p) = (p - c'_{i,t}(q_{i,t}(p))) \left(-D'_t(p) + \sum_{j \in \omega(i)} q'_j(p) \right). \quad \text{(S2)}$$

Eq. (S2) will typically have multiple solutions, however if the profit-maximizing generators are symmetric, then a unique symmetric equilibrium can be found by solving the following single differential equation:

$$q_t(p) = (p - c'_t(q_t(p))) \left(-D'_t(p) + (\hat{n} - 1) q'_t(p) \right), \quad \text{(S3)}$$

where $\hat{n}$ is the market Herfindahl-Hirschman index and the subscript i has been eliminated due to symmetry (*44*).

As shown in Table S1, Luminant and Texas Genco are roughly symmetric in that they own similar shares of generating capacity in the market. Moreover, the composition of their generator fleets (*i.e.* generating technologies and fuels used) is fairly similar. Thus we model these two firms assuming that they are symmetric and follow the equilibrium supply functions given by Eq. (S3).

Wind and Storage Optimization Model

Once we determine the supply functions submitted by the generators, we can define the price of energy in each hour in terms of net energy sales from wind and storage. If we let D_t denote the actual system demand in hour t, the hour-t energy price is given by:

$$p_t^*(X_t) = \min_p \left\{ p \,\middle|\, \sum_i q_{i,t}(p) = D_t - X_t \right\}. \tag{S4}$$

Note that this function is defined in the same manner (although with different supply functions) in both the competitive and oligopoly cases. We assume that wind and storage are used to maximize profits, while accounting for the effect of X_t on the price of energy. We formulate the wind and storage optimization problem by first defining the following model parameters:

κ: storage power capacity,

h: hours of storage,

η: roundtrip efficiency of storage,

ρ: wind production tax credit (PTC), and

$\bar{w}_t$: wind generation available in hour t.

We also define the following model variables:

v_t: total energy in storage at the end of hour t,

s_t: energy stored in hour t,

d_t: energy discharged from storage in hour t,

w_t: wind generation used in hour t, and

X_t: net energy sales in hour t.

The model is given by:

$$\max_{v,s,d,w,X} \sum_t p_t^*(X_t) \cdot X_t + \rho \cdot w_t \tag{S5}$$

$$\text{s.t.} \quad v_t = v_{t-1} + s_t - d_t \qquad \forall \ t \tag{S6}$$

$$X_t + s_t - d_t/\eta = w_t \qquad \forall \ t \tag{S7}$$

$$0 \leq w_t \leq \bar{w}_t \qquad \forall \ t \tag{S8}$$

$$0 \leq s_t \leq \kappa \qquad \forall \ t \tag{S9}$$

$$0 \leq d_t \leq \eta \kappa \qquad \forall \ t \tag{S10}$$

$$0 \leq v_t \leq h\kappa \qquad \forall \ t \tag{S11}$$

Eq. (S5) is the objective function, which maximizes profit from energy sales and the wind PTC, which we assume to be \$30/MWh. Eq. (S6) defines the storage level in each hour in terms of charging and discharging decisions and the previous hour's storage level. Eq. (S7) relates net energy sales in each hour to wind energy used and energy stored and discharged. Eq. (S8) through Eq. (S11) impose limits on the wind use, charging, discharging, and storage level variables in each hour, based on the output of the wind generator and technical characteristics of the storage plant. The model places no restriction that storage only be charged using wind energy—thus wind and storage could be a net buyer of energy if it charges more energy than wind produces in an hour.

This model assumes that the added wind and storage are operated by a single profit-maximizing firm. While Table S3 shows that wind assets were relatively concentrated in 2005, this assumption can overstate the extent to which wind and storage can exercise market power by adjusting sales to maximize profits. Relaxing this assumption would not affect wind generation, since wind is never curtailed under our single-firm assumption. This is because the wind PTC makes wind sufficiently valuable that it is never beneficial to curtail generation. Storage use could increase, however, since it is profit-maximizing to reduce storage use from a competitive level to maintain higher price difference between on- and off-peak periods (*20, 36*). Based on our findings, especially contrasting the emissions effects of storage in the competitive and oligopoly generation cases, it is likely that this greater use of storage would yield higher generator emissions.

Table S3: Breakdown of wind generation assets, on a capacity basis, in 2005. The remaining seven firms each own less than 5% of the wind capacity in the market.

Generating Firm	Generating Capacity (%)
FPL Group	33
Babcock and Brown	14
Shell Wind Energy	13
Desert Sky	9
Pecos Wind	9
Trent Wind	8

This optimization framework can also be used to model the wind-only case by setting $h = 0$. Similarly, by fixing $\bar{w}_t = 0$ in each hour, this problem can also model the storage-only case. In order to reduce computational complexity of the model, we use a quadratic approximation of the market price function, $p_t^*(X_t)$, (*24*). Moreover, we optimize the use of storage 24 hours at a time using a 48-hour optimization horizon (*20*). This use of a 48-hour optimization horizon ensures that energy is kept in storage at the end of each day if it has residual value by being used on the next day. The model is formulated deterministically, therefore we assume that the wind generator knows future wind availability.

Alternate Modeling Methods

Our modeling approach assumes that wind, storage, and conventional generators compete in the market in a sequential manner, with wind and storage being the first-movers. As noted above, we make this assumption since it allows us to model the behavior of the conventional generators in the oligopoly case using an SFE. Absent this assumption, the SFE model would not be valid due to dynamic interactions between different time periods. This sequential assumption may, however, overstate the dominance of wind and storage in the market. Thus it may be appropriate to model the market in the oligopoly case as a simultaneous-move game, for instance by assuming that generators, wind, and storage all behave as quantity-setting competitors in a Nash-Cournot game.

On the other hand, an SFE model yields a richer strategy space, which is also more reminiscent of actual electricity markets. Since it better represents the operation of actual electricity markets, we opt for the SFE-based model. Nevertheless, since the timing of market interactions can impact market outcomes, contrasting our results with a Cournot-type game would be a useful exercise, and is an area of future study.