Increasing the Value of Wind with Energy Storage☆

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Abstract

One economic disincentive to investing in wind generation is that the average market value of wind energy can be lower than that of other generation technologies. This is driven by the exercise of market power by other generators and the fact that the ability of these generators to exercise market power is inversely related to real-time wind availability. We examine the use of energy storage to mitigate this price suppression by shifting wind generation from periods with low prices to periods with higher prices. We show that storage can significantly increase the value of wind generation but the currently high capital cost of storage technologies cannot be justified on the basis of this use. Moreover, we demonstrate that this use of storage can reduce consumer surplus, the profits of other non-wind generators, and social welfare. We also examine the sensitivity of these effects to a number of parameters including storage size, storage efficiency, ownership structure, and market competitiveness—showing that a more-competitive market can make storage significantly more valuable to a wind generator.

Keywords: Wind energy, energy storage, electricity markets, imperfect competition, market power

1. Introduction

One economic disincentive to investing in wind generation is that the average value of wind energy can be lower than that of other generating technologies. This is because real-time wind availability can tend to be negatively correlated with energy prices. This issue is further exacerbated with market power, since the exercise of market power tends to be increasing in the demand for conventional generation, meaning that energy prices will be highest when wind output is lowest, and vice versa.[1] Green and Vasilakos (2010); Twomey and Neuhoff (2010) both examine this issue in the UK market using supply function equilibrium (SFE) and Cournot models, respectively. Green and Vasilakos (2010) show that depending upon the amount of wind available, the price of energy could be depressed by more than £65/MWh due to this effect that wind has on the market. Their analysis also shows that wind generators are subject to considerable risk due to the variability in wind availability with wind revenues varying by up to £50/kW-year. Twomey and Neuhoff (2010) compare average energy prices of wind and conventional generation, and show an average difference of more than £20/MWh in some instances.

One way that this price-suppressing effect of wind could be mitigated is by coupling energy storage with wind generation. A wind generator that has access to energy storage could shift wind generation from periods with low energy prices to periods with higher prices. Similarly, wind generation could be shifted away from periods in which high wind availability would suppress energy prices to periods in which higher loads or lower output mean that wind has less of a price-suppressing effect. It bears mentioning that the coupling of wind

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[1] It is very important to note that market power will tend to reduce the value of wind *relative* to conventional generators. Market power is, however, generally beneficial to a wind generator (compared to a more-competitive market), since the price of wind generation will tend to be higher in a less-competitive market.

generation and storage has been studied in other contexts, but that this proposed use of storage to increase the market value of wind energy has not be studied before. Sørensen (1981); Cavallo (1995); Denholm et al. (2005); Paatero and Lund (2005); DeCarolis and Keith (2006); Succar et al. (2006); Greenblatt et al. (2007); Swider (2007); Black and Strbac (2007); Abbey and Joos (2007); García-González et al. (2008); Arsie et al. (2009) all examine the value of using energy storage to manage the variable and unpredictable nature of wind availability in power systems and the broader economics of energy storage and wind. Most of this analysis has focused on more 'engineering' aspects of wind integration such as grid stability, load-balance, and system security. Some of these analyses have also shown benefits from using energy storage as an alternative to other dispatchable generators as a means of managing wind uncertainty, variability, and microturbulence. However other analyses, such as those of DeMeo et al. (2005, 2007), suggest that energy storage may not be necessary for these purposes until wind penetrations rise to levels higher than those seen in most power systems today. LCRA (2003); Denholm and Sioshansi (2009) consider the use of storage to increase the utilization of transmission assets by wind generators. They demonstrate that co-locating a storage device and wind generator on one side of a transmission line can allow the capacity of the transmission line to be reduced, since storage can be used to 'level' the output of the combined wind generator and storage device.

A downside to this use of storage is that the added flexibility that a wind generator would have in making generation decisions if it has access to energy storage could afford it added market power, potentially resulting in welfare losses. Bushnell (2003) demonstrates such a phenomenon with hydroelectric generators that have some flexibility in determining how much water to use for generation in each period—which is effectively a form of energy storage. His analysis shows that such generators may find it profitable to allocate more hydroelectric generation during off-peak hours, in order to reduce generation and keep energy prices higher during on-peak hours, yielding social welfare losses. Since energy storage would allow a wind generator to shift generation between periods, there is the potential for similar types of negative welfare impacts.

This paper examines the potential effects and interactions of large-scale wind and energy storage in the ERCOT (Texas) market. Using a Stackelberg-type SFE model to represent the behavior of generators, we show that the price of wind energy will tend to be below the average price of energy, and that this difference grows with the penetration of wind into the market. We demonstrate that a wind generator having access to energy storage can increase wind profits, but that this use of storage will result in higher consumer costs, lower conventional generator profits, and net social welfare losses. We also examine the sensitivity of these impacts of storage to several of our model assumptions such as market competitiveness and storage efficiency. We also consider the impacts of ownership structure on this value of storage, by comparing a case in which the wind generator owns and operates the storage to a case in which the storage is operated by an independent arbitrager, and show that the total value of storage is similar in these two cases. This raises a question of why we assume joint as opposed to disjoint ownership of storage and wind in our base case. As will be discussed in section 5.4, our results show that in the disjoint ownership case energy storage will be more valuable to a wind generator than to an arbitrager, and as such conjecture that it would be more likely to see a wind generator invest in storage. Moreover, our assumption of joint ownership follows modeling methodologies used in other analyses of wind and storage, such as the work of Denholm and Sioshansi (2009). The remainder of this paper is organized as follows: section 2 describes the model and data used in our analysis, section 3 summarizes the impacts of wind penetration and storage on wind profits while section 4 discusses the welfare effects of storage use. Section 5 discusses the sensitivity of our results to some of our modeling assumptions, and section 6 concludes.

It is important to note that our analysis focuses exclusively on the impact that high wind penetrations will have on suppressing the price and value of wind, and the potential value that energy storage could provide in mitigating these impacts. Thus, we ignore the impacts that wind uncertainty or variability would have on power system operations or on scheduling or contracting decisions made by a wind operator. Similarly, our analysis does not explore the benefits that storage could provide in mitigating these uncertainties. While energy storage could no doubt play a vital role in these capacities, the focus of our analysis is on the price effect of wind and our modeling assumptions reflect that. For instance, as is discussed in section 2, we assume that in cases in which the wind generator has access to energy storage, it has perfect foresight of future wind availability in making its storage decisions.

2. Model

Our model assumes that the market consists of three types of generators: the wind generator, a set of strategic conventional generators, and a competitive fringe of non-strategic conventional generators. Moreover, we consider cases in which the wind generator does and does not have access to energy storage and will also consider, in section 5, a case in which there is energy storage owned and operated by an arbitrager that is independent of the wind generator. We model the interactions between and decisions of the wind generator and conventional generators as a two-stage Stakelberg-type SFE model in which the wind generator is the leader and the conventional generators are followers. Thus, we assume that the wind generator first makes hourly decisions regarding its net energy sales in order to maximize its profits. These energy sales decisions will depend on real-time wind availability, whether it has access to energy storage, and how the market price will react to the wind generator's sales. Conventional generators then simultaneously submit supply functions to the market, which determine how the market price will react to the wind generator's sales. The strategic conventional generators are assumed to submit supply functions that maximize their expected profits, whereas the competitive fringe is assumed to submit supply functions based on marginal generation costs. Because of the sequential nature of the game we assume that the firms follow a subgame-perfect Nash equilibrium (SPNE), in which the strategic conventional generators determine profit-maximizing supply functions given the wind generator's energy sales and the supply functions of rival conventional generators, and the wind generator determines profit-maximizing energy sales given the expected SFE that will occur in the second stage of the game.

We rely on the assumption of a Stackelberg-type interaction between the wind and conventional generators because it allows us to model the behavior of the conventional generators using an SFE. Absent this assumption the SFE would not hold, since each conventional generator's residual demand function would be dependent on supply decisions made in other periods, as these decisions would influence the storage charging and discharging decisions. The Stackelberg assumption may, however, overstate the dominance of the wind generator in the market. Thus it may be appropriate to model the market as a simultaneous-move game, for instance by assuming the generators all behave as quantity-setting Cournot competitors. On the other hand, an SFE model yields a much richer strategy space, which is also more reminiscent of actual electricity markets, into which generators submit supply functions, than a Cournot model. Since it better represents the strategy space that generators compete in, we have opted for the SFE model. Nevertheless, since the timing of market interactions can impact theoretical market outcomes, contrasting our results with a simultaneous Cournot-type game would be a useful exercise, and is an area of future study.

In order to solve for an SPNE we use backward induction and begin by considering the SFE between the conventional generators.

2.1. Stage 2: Supply Function Equilibrium

In the second stage of the game the conventional generators submit supply functions, which specify the quantity of energy that they are willing to supply to the market at each given price. Klemperer and Meyer (1989), who first develop the SFE model, assume firms compete in supply functions because of uncertainty in the residual demand that they will serve. This demand uncertainty allows the firms to derive supply functions that give a profit-maximizing price/quantity pair for each possible demand realization. Green and Newbery (1992) apply the SFE model to the British electricity market and note that the demand uncertainty assumption is equivalent to the fact that generators in spot markets must commit to a fixed supply function for a period of time during which there are a number of settlements with different and uncertain demand. For example, Sioshansi and Oren (2007); Hortaçsu and Puller (2008), who empirically validate the SFE model in the ERCOT market, note that generators submit supply functions that are fixed for an entire hour, during which the market settles at four 15-minute intervals. Because the exact demand for spot energy in these four settlement periods is uncertain, this is equivalent to the uncertainty assumption of Klemperer and Meyer (1989). It is important to note that although electricity demand can be forecast fairly accurately hour-ahead, there is nonetheless some demand uncertainty and this uncertainty will yield a non-trivial SFE so long as the demand can take on different values with some non-zero probability (regardless of how small those probabilities may be). Moreover, because real-time wind availability is also somewhat uncertain, the presence of the wind generator and its sales decisions will add to the demand uncertainty that the strategic firms face since the strategic firms will view wind sales as a shift in their residual demands.

Equilibrium supply functions are obtained from the strategic firms' profit-maximization problem. Firm i's profit maximization is given as:

$$\max_{p} \ \pi_i(p,t) = p \cdot \left(D(p,t) - \sum_{j \neq i} q_j(p) \right) - c_i \left(D(p,t) - \sum_{j \neq i} q_j(p) \right), \tag{1}$$

where p is the market price, $D(p,t)$ is the market demand function at time t, $q_j(p)$ is firm j's supply function, and $c_i(\cdot)$ is firm i's cost function. Manipulating the first-order necessary condition (FONC) of equation (1) gives a set of coupled differential equations characterizing an SFE. Firm i's FONC becomes:

$$q_i(p) = (p - c_i'(q_i(p))) \left(-\frac{\partial}{\partial p} D(p,t) + \sum_{j \neq i} \frac{d}{dp} q_j(p) \right). \tag{2}$$

As discussed by Klemperer and Meyer (1989); Baldick and Hogan (2002); Holmberg (2007, 2009), one of the difficulties with the SFE model is that there is typically not a unique equilibrium, and asymmetric SFE can be difficult to compute. Green (2008) shows how to derive a unique equilibrium assuming the strategic firms are symmetric, in which case differential equation (2) becomes:

$$q_i(p) = (p - c_i'(q_i(p))) \left(-\frac{\partial}{\partial p} D(p,t) + (\hat{n} - 1) \frac{d}{dp} q_i(p) \right), \tag{3}$$

where $\hat{n}$ is the inverse of the industry Herfindahl-Hirschman index (HHI). Because the HHI is computed empirically based on the market shares of the strategic firms, $\hat{n}$ is not restricted to take an integer value.

Following Sioshansi (2010a) the conventional generators in ERCOT are modeled using the generator set, operating costs, and loads from 2005. Based on empirical evidence given by Sioshansi and Oren (2007); Hortaçsu and Puller (2008) and following Sioshansi (2010b) the market is assumed to have two strategic generating firms—TXU and Texas Genco—which are roughly symmetric and for which equilibrium supply functions are derived. The remaining conventional generators are assumed to behave competitively and offer their generation on the spot market at marginal cost. Therefore these remaining firms constitute the competitive fringe and their competitive supply functions are used to determine the hourly price-elastic demand functions as:

$$D(p,t) = D_t - \sum_{k} s_k(p,t), \tag{4}$$

where D_t is the total metered demand in hour t and $s_k(p,t)$ is the supply function of the k^{th} firm in the competitive fringe. These computed demand functions are then used in equations (1) through (3), and it is important to note that we use only the supply functions of the competitive fringe (as opposed to forward contracting) to compute the price-elastic demand function. The approximately 2 GW of wind that was operating in ERCOT in 2005 is included in the generation portfolios of the firms that it was owned by in 2005. As is discussed below, our analysis of the price and profit effects of higher wind penetrations will focus on up to an additional 10 GW of wind being added to the ERCOT system. Thus, our analysis of the value of wind and energy storage focuses on the economic performance of this additional wind capacity.

Conventional generators' costs are computed using engineering estimates, with heat rate and fuel cost data obtained from Ventyx and Platts. Because fuel costs generally vary on a daily basis, we compute an SFE for each day in our sample. Nuclear generators and wind generators that existed in 2005 are assumed to be operated as must-run units by the system operator, and to not be bid strategically by the generators. Real-time wind availability of wind plants that existed in 2005 is based on hourly modeled historical mesoscale data for 2005 provided by 3TIER. Each wind generator is associated with the location in the 3TIER data that is geographically closest and the associated modeled data is used to determine real-time wind availability from that wind plant.[2] Hourly metered load data, as reported by ERCOT, is combined with the marginal cost functions of the competitive fringe and nuclear output to determine the demand function, $D(p, t)$, as given in equation (4).

2.2. Stage 1: Wind Optimization

In the first stage of the game the wind generator decides how much wind to sell and, in the cases in which it has access to energy storage, how to operate the storage. We assume that the wind generator anticipates the SFE that will occur in the second stage of the game and determines its wind sales and storage operations to maximize profits given how its net wind sales and the SFE will determine the price of energy. Moreover, because the case in which the wind generator does not have access to energy storage can be likened to the wind generator having a storage device with zero capacity, this model can, without loss of generality, be applied in cases with and without energy storage.

The supply functions of the conventional generators from the second stage of the game can be combined with the actual electricity demand to determine a market price function, which gives the price of energy as a function of net energy sold by the wind generator. If we let x denote the wind generator's net energy sales and $s_i(p)$ represent conventional generator i's supply function, then the market price function in hour t is defined as:

$$p_t(x) = \inf \left\{ p \;\middle|\; D_t \leq x + \sum_i s_i(p) \right\}. \tag{5}$$

This market price function can then be combined with real-time wind availability data and characteristics of the energy storage to model the profit-maximizing co-optimization of the wind and storage. In order to give the formulation of the model, we first define the following model parameters:

- T: number of hours in planning horizon
- κ: storage power capacity (MW)[3]
- h: hours of storage[4]
- η: roundtrip efficiency of storage
- X: wind production tax credit (\$/MWh)
- $\bar{w}_t$: wind generation available in hour t

We then define the following decision variables:

- l_t: storage level at the end of hour t
- s_t: energy put into storage in hour t
- d_t: energy taken out of the storage in hour t
- w_t: wind used in hour t
- σ_t: net energy sales in hour t

[2]Alternatively, actual generation data from 2005 could be used for these wind generators. We opt not to use this approach, however, because actual generation data is censored due to transmission-related wind curtailments, which, as discussed by LCRA (2003); Sioshansi and Hurlbut (2010), were non-trivial during this period.

[3]Our model assumes that the storage has the same charging and discharging capacity. Greenblatt et al. (2007) note that many modern storage devices can easily be designed with different charging and discharging capacities.

[4]While some authors define 'hours of storage' as the number of hours the storage device can be discharged at maximum capacity, we define it as the number of hours the device can be charged at maximum capacity.

The formulation of the model is then given as:

$$
\begin{aligned}
\max \quad & \sum_{t=1}^{T} p_t(\sigma_t) \cdot \sigma_t + X \cdot w_t && && (6)\\
\text{s.t.} \quad & l_t = l_{t-1} + s_t - d_t && \forall\ t = 1, \ldots, T && (7)\\
& \sigma_t + s_t - d_t/\eta = w_t && \forall\ t = 1, \ldots, T && (8)\\
& 0 \le w_t \le \bar{w}_t && \forall\ t = 1, \ldots, T && (9)\\
& 0 \le s_t \le \kappa && \forall\ t = 1, \ldots, T && (10)\\
& 0 \le d_t \le \eta\kappa && \forall\ t = 1, \ldots, T && (11)\\
& 0 \le l_t \le h\kappa && \forall\ t = 1, \ldots, T && (12)
\end{aligned}
$$

Constraint (7) defines the storage level in each hour as a function of the previous storage level and charging and discharging decisions made. Constraint (8) defines energy sales in terms of wind use and storage decisions. Constraint (9) limits wind generation based on actual wind availability, while constraints (10) through (12) are power and energy capacities on storage.

We assume that the wind generator optimizes the dispatch of storage over the year one day at a time, using a rolling two-day optimization horizon. As discussed by Sioshansi et al. (2009), the two-day optimization horizon is used to ensure that the storage is not fully discharged at the end of each day, which would be optimal behavior if a one-day optimization horizon is used. The starting storage level at the beginning of each day is fixed based on the ending storage level of the previous day (except that we assume that storage is empty at the beginning of the first day of the year). Thus stored energy is not 'lost' between days. Moreover, because there is no value in keeping energy in storage at the end of the last day of the year, storage is always optimally empty at the end of the year. We further assume that the wind generator has perfect foresight of wind availability and the market price function.

We consider cases in which the wind generator owns up to 10 GW of nameplate wind capacity. We determine the real-time availability of wind from the hourly historical mesoscale model data provided by 3TIER. We assume that the additional wind generators will be located at the same sites as actual and planned wind installations in ERCOT between 2005 and 2011, and assume that the incremental capacity is distributed in proportion to the planned capacities at these sites. These sites are then associated with the 3TIER data based on geographic distance, and the real-time wind availabilities of the incremental wind generators are scaled based on the assumed nameplate capacity. It is worth noting that because we assume the incremental wind capacity at these sites will be scaled in proportion to planned wind installations, we are not fully capturing potential mitigation of wind resource variability through geographic aggregation. However, because the focus of our analysis is on the price effect of wind as opposed to wind variability, this assumption is justified. We also assume that the wind generator will be eligible for the \$19/MWh production tax credit (PTC) for all of the wind that it uses, and that this PTC applies to wind energy that is put into storage.

Because the equilibrium supply functions given by equation (3) will generally be nonlinear, the market price function will be nonlinear as well. In order to reduce the complexity of the wind generator's profit-maximization problem, we approximate the market price function as a quadratic polynomial by ordinary least-squares. Figure 1, which shows the actual computed market price function and quadratic approximation, shows the approximation to be a relatively good fit. The wind generator's profit-maximization problem is formulated using AMPL 11.21 and solved using ipopt 3.5.4 (Fourer et al. (2002); Wächter and Biegler (2006) provide details on the software packages). Because the market price function is assumed to be quadratic, the profit-maximization problem will be non-convex. As such, we are not guaranteed to have found a global maximum of the wind generator's profit-maximization problems and our estimates may understate the value or effects of energy storage. Thus our results should be viewed as providing a lower-bound on the value of storage.

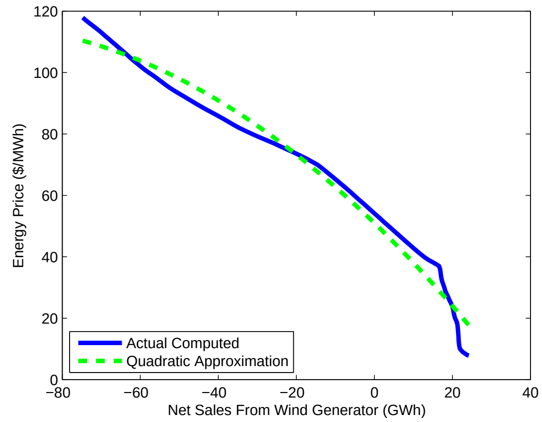

Figure 1: Actual computed market price function and quadratic approximation for hour 1 of 1 January, 2005.

3. Price of Wind and Value of Storage

Table 1 demonstrates the effect of energy prices responding to wind generation by showing the energy-weighted average price of wind energy and the average load price, for the case in which there is no storage. By comparison, the average price of wind energy and the average load price are $92.48/MWh and $98.94/MWh, respectively, if prices are fixed.[5] The table shows that in all cases and even with fixed prices, the price of wind generation tends to be lower than the overall average. With wind-responsive prices, introducing wind to the system suppresses energy prices—which is shown by a 5.7% decrease in the average load price with 10 GW of added wind. Because the price-suppressing effect of wind is concentrated in hours in which there is wind available, the effect is more pronounced for wind energy. For example, adding 10 GW of wind reduces the price of wind by 13.1%. These results are consistent with the findings of Green and Vasilakos (2010); Twomey and Neuhoff (2010). Figure 2 summarizes the effect that this price-suppression has on the incremental wind generator's profits by comparing profits in the fixed- and responsive-price cases. The figure shows absolute profit losses between these two cases, and relative profit losses as a percentage of the profits that would be earned with fixed prices. The results show that responsive prices can diminish the value of a wind generator by close to 11%, translating into an annual loss of more than $350 million.

Table 1: Average price of wind energy and average load price with wind-responsive prices. For comparison, with fixed prices the average price of wind energy is $92.48/MWh and the average load price is $98.94/MWh.

Wind Capacity (MW)	Wind Price ($/MWh)	Load Price ($/MWh)
1000	91.41	98.44
2000	90.31	97.92
3000	89.19	97.39
4000	88.03	96.85
5000	86.84	96.30
6000	85.62	95.74
7000	84.36	95.16
8000	83.06	94.57
9000	81.73	93.96
10000	80.37	93.34

Figure 3 shows the annual value to the wind generator of different amounts of energy storage assuming wind-responsive prices. The value of storage is defined as the increase in the annual profits of the wind

[5] In order for the fixed- and responsive-price cases to be comparable, the fixed prices are calculated from the market price function, but assuming that prices do not respond to wind generation (i.e. assuming that prices are fixed at $p_t(0)$ in each hour).

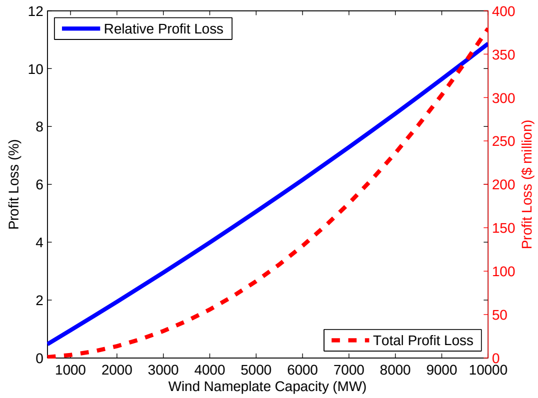

Figure 2: Wind generator's profit losses from wind-responsive prices. Total profit loss is defined as the difference in profits between the fixed- and responsive-price cases, relative profit losses gives this difference as a percentage of profits in the fixed-price case.

generator with storage compared to the no-storage case. This profit increase is due to the ability of energy storage to shift wind generation to higher-priced periods and partially mitigate the price-suppressing effect of wind. The figure assumes the wind generator has 10 GW of wind capacity and that the energy storage has a power capacity between 500 and 10000 MW, between 1 and 20 hours of storage, and a roundtrip efficiency of 0.8. As Sioshansi et al. (2009) note, depending on the underlying technology, storage devices can range between the sizes that we consider here. They also note that 0.8 is a reasonable storage efficiency, but is at the upper end of storage technologies available today (we consider the effect of storage efficiency further in section 5). The figure also assumes a no-arbitrage restriction, which limits the wind generator to use storage solely for shifting of wind generation between periods as opposed to for energy arbitrage purposes, on the use of storage. This restriction is imposed in the wind generator's profit-maximization problem by adding the constraint:

$$s_t \leq w_t \quad \forall\, t = 1, \ldots, T. \tag{13}$$

We impose this constraint because the focus of our analysis is on the use of storage to increase the value of wind generation and not on the value of arbitrage.[6] We do, however, relax this constraint as part of our sensitivity analysis in section 5 to capture the added value that arbitrage could provide a wind generator.

The figure shows that energy storage can play a noticeable role in increasing the market value of wind generation and the profitability of a wind generator. The smallest storage size that we consider, 500 MW with one hour of storage, increases the average selling price of wind by $0.22, which translates into a $3.8 million increase in annual revenues of the wind generator. The largest storage size, 10 GW with 20 hours of storage, increases the selling price of wind by $5.16, resulting in a $74.4 million increase in annual revenues. The figure also shows that the ability of storage to increase the profits of the wind generator reaches a 'saturation frontier,' which is roughly in the shape of a parabola going through storage sizes of 5000 MW with 20 hours of storage, 6000 MW with 10 hours of storage, and 10000 MW with 6 hours of storage. Although the selling price of wind and wind profits are increased with amounts of storage above this parabola, the incremental increases are small compared to the gains from smaller storage sizes.

Figure 4 summarizes the value of 500 MW of storage with eight hours of storage to different-sized wind generators, assuming the no-arbitrage restriction is still in place. The value of storage is given in both absolute terms and as a percentage of the profit losses between the fixed- and responsive-price cases. The fact that storage value is strictly increasing and non-diminishing in the capacity of the wind generator,

[6]It is important to note that we do not advocate such a use of a storage, since storage has many potential and valuable applications, as surveyed by Eyer and Corey (2010). Rather, we impose the constraint due to the focus of our analysis. Indeed, one could argue that even if we included arbitrage in this 'base case,' it would understate the value of energy storage, since storage could be used for ancillary service, capacity, transmission, and many other applications.

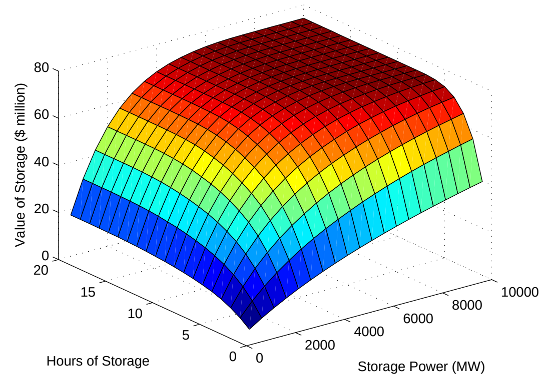

Figure 3: Annual value of storage to a 10 GW wind operator assuming wind-responsive prices and no arbitrage. Storage value is defined as the increase in the wind generator's total annual profits when it has access to storage.

despite the modest amount of storage, shows that the wind generator does not 'saturate' the ability of storage to provide value. Rather, the ability to influence market prices through the use of storage becomes increasingly valuable to a larger wind generator regardless of the relative sizes of storage and the generator. Moreover, the figure shows that for smaller-sized wind generators, the increase in profits from generation shifting outweighs the profit loss from wind-responsive prices, which is shown by the greater than 100% profit increases for small wind generator sizes.

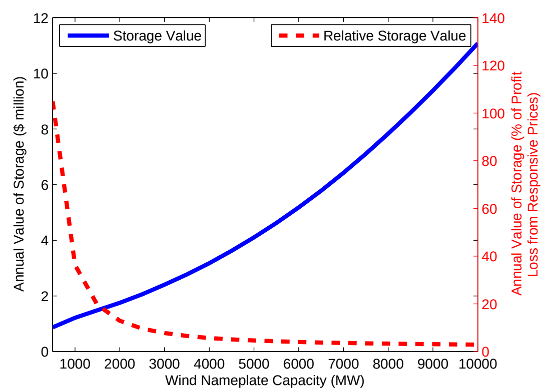

Figure 4: Value of 500 MW of storage with eight hours of storage assuming wind-responsive prices and no arbitrage. Storage value is defined as the increase in the wind generator's total annual profits when it has access to storage. Relative storage value gives this increase as a percentage of the profit losses shown in figure 2.

One natural question that arises from this analysis, and especially figure 3, is what amount of storage can be economically justified based on the increase in wind profits or at what cost storage investments can be justified. This type of analysis would require comparing the capital cost of storage to several year's worth of revenue streams, which presents some complications. One is that it has been some time since utility-scale energy storage has been built in the United States, and there are a wide range of estimates for the capital cost of storage. Moreover, most cost estimates are site-specific since some storage technologies, such as pumped hydroelectric storage (PHS), require specific geological conditions. Despite these caveats, some capital costs estimates, such as those of Deane et al. (2010), do exist. Recent estimates of PHS capital costs (in 2005 dollars) are in the range of $1355–1806/kW, while the cost of compressed-air energy storage (CAES) is estimated to be in the $677–903/kW range. It is important to note, however, that CAES is a very different storage technology from what we have modeled here since CAES is a hybrid technology that uses natural gas when discharging, and as such incurs a non-trivial variable operating cost (Succar and Williams (2008) provide a more detailed description of CAES technology). Thus it is not strictly correct to compare the storage values we have estimated to the capital cost of CAES—instead we would have to account for the impact of natural gas costs on the optimized operation and value of CAES, which would likely be lower than the pure storage technology we have modeled. We nevertheless include CAES in this cost analysis simply for comparative purposes, since CAES is currently the storage technology with the lowest capital cost. Moreover, although other storage technologies, such as electrochemical energy storage exist, the capital cost of these technologies are much higher than those of PHS and CAES, and as such we exclude these from consideration here.

The second complication with our cost analysis is that it would require making assumptions about several years worth of energy prices and wind conditions. Rather than making these assumptions about future conditions, we opt to present a year-1 breakeven cost, assuming an 11% capital charge rate (CCR). This CCR is meant to capture all of the various financing parameters involved in storage investment and converts the total capital cost of storage into an annual cost of financing an investment in storage (Denholm and Sioshansi (2009) further discuss this use of the CCR). Using this CCR, the breakeven cost of energy storage is computed by dividing the annual values of storage given in figure 3 by 0.11—which amounts to a roughly factor of nine increase in the annual storage value. Thus, depending upon the size of storage, these breakeven costs range between \$34 million and \$676 million. When translated to a per-kW basis, the highest breakeven cost of storage for a 10 GW wind operator is \$317/kW, which is for 500 MW of storage with 20 hours of storage and is much lower than current energy storage cost estimates—implying such an investment in storage would not be prudent. It is important to note, however, that because storage can be put to multiple uses, such as reducing transmission capacity requirements of the wind generator and reducing uncertainty in wind output, the value of storage and associated breakeven cost can be higher than the value estimates given in figure 3. Moreover, since we have excluded other market services, such as arbitrage or ancillary services, the value of storage may be even higher. For instance, Denholm and Sioshansi (2009) show that it can be economic to use energy storage to reduce transmission requirements for a wind generator. If this wind generator also faces wind-responsive prices, the value of this energy storage could be higher since the storage could provide an additional service. On the other hand, multiple uses of storage may 'compete' with each other, resulting in subadditive value. For instance, if storage is being used to level the output of a wind farm to reduce transmission capacity requirements, this may interfere with the use of storage to reduce the price-suppression effect.

4. Impact of Wind and Storage on Welfare

Although the price-suppressing effect of wind will reduce the market value of wind and wind profits, these price changes will also affect conventional generators and consumers. Conventional generators will generally see their profits reduced due to lower demand for conventional energy (since more wind energy will be available) and their generation commanding a lower price. Consumers, on the other hand, will generally see their energy costs decrease. Moreover, because the value of energy storage to a wind operator is that it increases the market price of wind, this use of storage will negate some of these external welfare effects of wind.

Figure 5 summarizes the welfare effects that wind-responsive prices have on the three entities affected: wind generators, conventional generators, and consumers. The welfare change of wind and conventional generators are defined as the difference between the total annual profits of the two groups with fixed and wind-responsive prices. Because energy prices are lower with wind-responsive prices, both wind and conventional generators have annual welfare losses for all wind capacities. The change in consumer welfare is computed as the difference in the cost of serving consumer loads with fixed and wind-responsive prices, since this generation cost is passed onto consumers through their electricity tariffs. Because wind-responsive prices are lower than fixed prices, consumers have an annual welfare gain due to lower total energy costs. The line in figure 5 shows the total welfare change, which is defined as the sum of welfare changes to the three groups. The line shows that while most of the welfare changes are wealth transfers from wind and conventional generators to consumers, there are some net welfare gains of up to \$50 million with 10 GW of wind, which is indicated by the fact that the line is always slightly greater than zero.

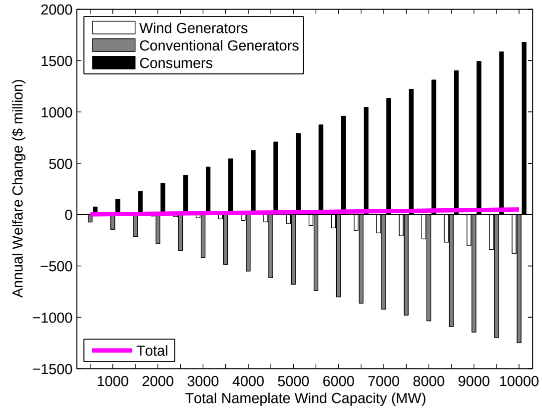

Figure 5: Annual generator and consumer welfare changes between fixed- and responsive-price cases. Wind and conventional generator welfare changes are defined as the difference in firm profits between the two cases. Consumer welfare change is defined as the difference in total energy costs between the two cases.

When storage is added to the system, the wind operator will generally use it to increase the value of wind, which will tend to increase the overall load price. Figure 6 summarizes the welfare effect of adding energy storage to the market by comparing generators' profits and consumer costs with 10 GW of wind and storage to a case with 10 GW of wind and no storage. The figure assumes that prices are wind-responsive, the no-arbitrage constraint is still imposed, and considers a case with eight hours of storage with power capacities ranging between 500 MW and 10000 MW. As with figure 5, the changes in the generators' welfares are computed as the change in their profits, whereas the change in consumer welfare is computed as the change in energy costs (between the cases with and without energy storage).

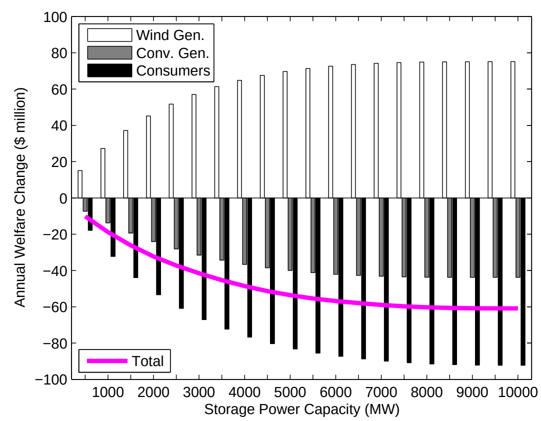

Figure 6: Annual generator and consumer welfare changes with eight hours of storage with 10 GW of wind, assuming wind-responsive prices and no arbitrage. Wind and conventional generator welfare changes are defined at the difference in firm profits between the storage and no-storage cases. Consumer welfare change is defined as the difference in total energy costs between the two cases.

Figure 6 shows that adding storage to the market has the effect of increasing the wind generator's profits (as was also shown in section 3) but decreasing consumer welfare and the profits of conventional generators. The decrease in consumer welfare should be fairly intuitive—because the wind generator uses storage to increase the selling price of its wind energy, this will reduce the price-suppressing effect of wind resulting in higher energy costs and a welfare loss to consumers. The loss of conventional generator surplus is, however, not as intuitive. Because energy storage will increase the average price of energy, this will tend to increase conventional generators' energy revenues, and this is observed in our results. Moreover, because energy storage incurs efficiency losses when wind energy is put through the storage cycle, adding energy storage will also increase the total volume of sales from conventional generators. However, because energy storage is used to shift wind generation from lower- to higher-priced hours, this implies that the increases in conventional generation will be concentrated in hours with lower prices and with a lower energy price markup over cost (due to the nature of an SFE). Conversely, most of the decreases in conventional generation will be concentrated in hours with higher prices and a higher energy price markup over cost. Thus, although the use of energy storage increases the revenues of conventional generators, the associated increases in generation cause an even larger increase in generation costs, due to the generation increases being concentrated in hours during which the energy price markup over cost is lower.

To demonstrate this phenomenon more concretely, table 2 compares the energy price and average conventional generation cost with and without 10000 MW of storage with eight hours of storage, assuming 10 GW of wind is in the system. When storage is added to the system, the resulting change in the output of the combined wind generator/storage operator causes conventional generators to increase their output in 2421 hours of the year and yields a gross generation increase of 5117 GWh from the conventional generators during these hours (compared to the no-storage case). Similarly, in 2320 hours of the year conventional generators reduce their output by a total gross amount of about 4094 GWh. Thus, when these increases and decreases in generation are taken into account, the conventional generators have a net increase in output of about 1023 GWh, due to the efficiency losses associated with wind energy being put through the storage cycle. However, the average price of energy during hours in which the output of the conventional generators decrease is about \$95.89/MWh whereas they incur an average cost of about \$70.21/MWh. Conversely, the average energy price during hours in which the output of conventional generators increase is about \$77.26/MWh whereas they incur an average cost of about \$59.23/MWh. Thus, the use of storage causes about 4094 GWh of generation to be shifted from hours with an average profit margin of about \$25.68/MWh to hours with an average profit margin of about \$18.03/MWh, yielding the overall welfare loss. Smaller-sized storage devices will have a similar effect, although the scale of the losses to conventional generators will be smaller due to the fact that a smaller amount of storage will not allow as much generation and price shifting to take place.

Table 2: Differences in dispatch, selling price, and average generation cost of conventional generators due to energy storage, assuming 10 GW of wind, wind-responsive prices, and no arbitrage. Differences given are between no-storage and 10 GW of storage with eight hours of storage cases.

	Conv. Gen. Increase	Conv. Gen. Decrease
Number of Hours	2421	2320
Gross Generation Change (GWh)	5117	4094
Average Energy Price (\$/MWh)	77.26	95.89
Average Generation Cost (\$/MWh)	59.23	70.21
Average Profit Margin (\$/MWh)	18.03	25.68

Thus, figure 6 shows that the net welfare effect of adding storage to the system will be to decrease profits of conventional generators, increase consumers costs, and increase wind profits. Moreover, the line in figure 6 gives the change in total welfare, showing a net social welfare loss when storage is added.

5. Sensitivity of Storage Value to Model Assumptions

Because the value of storage and our results will be dependent on the assumptions underlying our model, we repeat the analysis to determine their sensitivity to storage efficiency, the competitiveness of the market, the ability of the wind generator to use storage for arbitrage, and storage ownership structure.

5.1. Storage Efficiency

As Sioshansi et al. (2009) note, the 80%-efficient storage that we have assumed thus far is toward the upper-end of modern storage devices, with PHS having efficiencies in the range of 65–85% and large battery systems having efficiencies of around 65–75%. As such, we consider the effect of storage efficiency on its value to a wind generator. Figure 7 summarizes the effect of storage efficiency on storage value, by showing the reduction in storage value between lower- and 80%-efficient storage. The loss in value is given as a percentage of the value of 80%-efficient storage, and assumes the wind generator has 10 GW of wind capacity and that there are eight hours of storage—fewer and more hours of storage show very similar results. The figure shows that storage value is highly sensitive to its efficiency. For instance, reducing the efficiency of a 1000 MW device by 12.5% from 0.8 to 0.7 reduces the value of storage by 41.8%. This sensitivity to the efficiency of the device is also observed by Sioshansi et al. (2009) in the context of arbitrage value. They attribute the sensitivity to the fact that a more inefficient device must charge more hours to discharge a given amount, and that these additional hours in which it must charge will be more expensive. In our context a related phenomenon occurs: we still have that a less-efficient device must charge more hours for a given discharge, but we also have that when the price of energy is suppressed by wind generation the alternative of putting wind into storage is less attractive, since more energy will be lost due to efficiency losses.

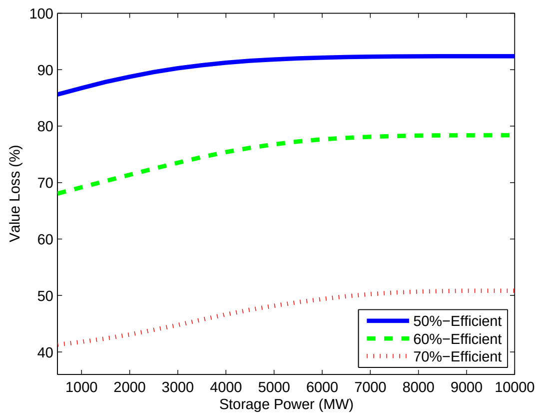

Figure 7: Loss in value of lower-efficiency storage device as compared to an 80%-efficient device assuming 10 GW of wind, eight hours of storage, wind-responsive prices, and no arbitrage.

5.2. Market Competitiveness

Another sensitivity we consider is the competitiveness of the market in which the wind generator is participating. Our analysis thus far has assumed a market with two strategic conventional generators (because $\hat{n}$ is computed based on the actual market shares of the two firms, our analysis has used $\hat{n} = 1.97$ in equation (3)), which will tend to result in comparably high exercise of market power. The effect of this market power will be that energy prices will tend to be much higher than marginal cost in periods in which conventional generating loads are high, which will also tend to be periods in which wind availability is low. In a more competitive market, by contrast, energy prices will tend to be comparably closer to marginal cost, even when conventional generating loads are high and will spike only during hours with extremely high demand peaks. We repeat our analysis for a case in which the market has six symmetric strategic conventional generators. We derive the cost functions of the strategic generators from the same cost estimates for TXU and Texas Genco (i.e. we use the same cost function for the strategic generators in this case as in the duopoly case), but assume that $\hat{n} = 6$ in equation (3). We also use the same demand values and competitive fringe to derive the price-elastic demand functions, $D(p, t)$.

Figure 8 summarizes the effect that this more-competitive market has on the value of wind generation and storage by showing the average price of wind from a 10 GW generator, assuming wind-responsive prices and no arbitrage, and with different amounts of energy storage. The more-competitive market tends to have lower prices overall, because the strategic firms have less opportunity to exercise market power. This effect will also reduce the overall value of wind generation. For example, without storage the average energy price for a 10 GW wind generator drops to \$58.13/MWh, compared to an average price of \$80.37/MWh in the duopoly case. On the other hand, the value of storage is significantly higher in the more-competitive market because there is added value in the wind generator being able to shift its generation to periods with extremely high loads, which will have higher energy price peaks (although not as high as in the duopoly case). This is shown by the fact that in the duopoly case 10 GW of storage with 20 hours of storage only increases the average selling price of wind by about \$5.16/MWh, as opposed to an average wind price increase of \$13.18/MWh in the six-firm case. Moreover, comparing figure 8 to 3 shows that in the more competitive market the value of storage does not plateau (over the range of storage sizes that we consider) as it does with a duopoly, since the average wind price does not plateau with larger storage sizes.

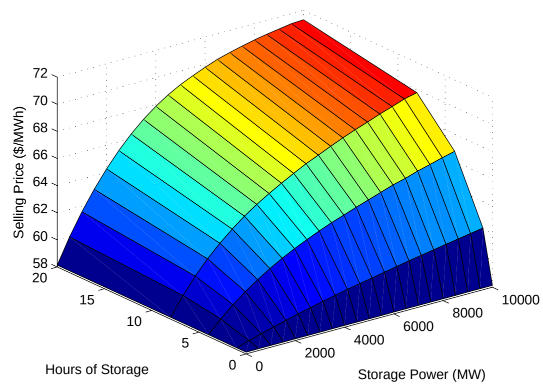

Figure 8: Average selling price of generation from a 10 GW wind generator with different amounts of storage assuming wind-responsive prices, no arbitrage, and six symmetric strategic generating firms in the market.

It is also interesting to note that in this more competitive case, the year-1 breakeven cost of 500 MW of storage with 20 hours of storage, assuming the same 11% CCR, is \$756.74/kW, which is much closer to the cost estimate of PHS. Moreover, this breakeven cost is within the range of cost estimates for CAES, although it is again important to stress that our model has assumed a pure storage technology. Thus, a more complete analysis that considers the hybrid nature of CAES would be needed to determine whether CAES would be an economic investment for these purposes.

5.3. Energy Arbitrage

The next model sensitivity that we consider is the value of allowing the wind generator to use storage both for energy arbitrage and to store wind. As discussed above, we impose constraint (13) on the wind generator's profit-maximization problem in the base case to ascertain the value to a wind generator of using storage exclusively for storing wind and reducing the price-suppressing effect of wind. In practice, however, a wind generator could use storage for arbitrage in addition to storing wind.[7] Figure 9 summarizes the arbitrage value of a storage device owned by a 10 GW wind operator, which is defined as the increase in profit when constraint (13) is relaxed in the wind operator's profit-maximization problem. The figure shows that a wind generator can make use of the storage device for arbitrage, although the value of this arbitrage is two orders of magnitude smaller than the value of using storage for the shifting of wind generation. Moreover, the value of arbitrage has a similar plateauing effect to that seen before, in that for a 7 GW or larger storage device there is no added value from increasing the hours of storage above eight. This plateauing effect is likely due to the assumption that the dispatch of storage is optimized using a rolling two-day planning horizon. If storage use is being optimized over a longer period, such as a week or two, additional hours of storage can allow for more interday arbitrage.

[7]As implied above, a wind generator may have even more lucrative options available. For instance, Walawalkar et al. (2007) show that providing regulation services can be more profitable than energy arbitrage.

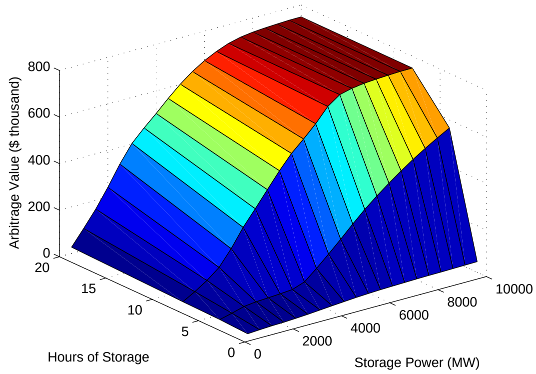

Figure 9: Annual arbitrage value of storage to a 10 GW wind generator assuming wind-responsive prices. Arbitrage value is defined as the increase in profits when the no-arbitrage constraint is relaxed in the wind generator's profit-maximization problem.

5.4. Storage Ownership

Another question raised by our analysis of wind and storage is whether the same effects of storage could be achieved if storage is owned by a separate and independent entity that uses storage solely for arbitrage purposes. Indeed, one might argue that this model of disjoint ownership would be a better case to consider than a joint wind and storage operator, since a wind generator may not wish to invest in energy storage. When storage is owned by a separate entity, the market and the price of energy will dictate the decisions that the storage operator makes and the interactions between wind and storage. For instance, the energy price will be suppressed during hours with abundant wind availability, due to the wind generator having to sell its energy. However, the storage operator would charge its storage during these hours due to the relatively low price of energy. Conversely, hours with low wind availability will have comparably higher energy prices and as such the storage operator would discharge storage during such hours. Thus, the price impacts of wind and profit-maximizing storage operations can help yield a similar outcome to what would occur with joint ownership of wind and storage.

This situation of disjoint storage ownership can be modeled by assuming that the wind generator and storage operator simultaneously make their wind generation and storage decisions in stage 1 of the game. If we define γ_t to be net energy sales from the storage operator, the wind generator's profit-maximization problem is given by:

$$\max_{w_t} \quad \sum_{t=1}^{T} [p_t(\gamma_t + w_t) + X] \cdot w_t \tag{14}$$

$$\text{s.t.} \quad 0 \leq w_t \leq \bar{w}_t \qquad \forall\, t = 1, \ldots, T \tag{15}$$

where constraint (15) bounds wind generation in each hour based on real-time wind availability. The storage operator's profit-maximization problem is given by:

$$\max_{\gamma_t, s_t, d_t, l_t} \quad \sum_{t=1}^{T} p_t(\gamma_t + w_t) \cdot \gamma_t \tag{16}$$

$$\text{s.t.} \quad l_t = l_{t-1} + s_t - d_t \qquad \forall\, t = 1, \ldots, T \tag{17}$$

$$\gamma_t = d_t/\eta - s_t \qquad \forall\, t = 1, \ldots, T \tag{18}$$

$$0 \leq s_t \leq \kappa \qquad \forall\, t = 1, \ldots, T \tag{19}$$

$$0 \leq d_t \leq \eta\kappa \qquad \forall\, t = 1, \ldots, T \tag{20}$$

$$0 \leq l_t \leq h\kappa \qquad \forall\, t = 1, \ldots, T \tag{21}$$

where constraint (17) defines the storage level in each hour, constraint (18) relates energy sales to storage decisions, and constraints (19) through (21) are storage energy and power constraints. In order to find a Nash equilibrium of the wind generator's and storage operator's problems, we can iteratively solve the two optimization problems until arriving at a set of decision variables such that neither the storage operator nor wind generator would unilaterally deviate.[8]

Figure 10 summarizes the effect of joint versus disjoint ownership of wind and storage on the total profits of the wind generator and storage operator. The figure shows the increase in total profits from joint ownership (above the sum of profits from disjoint ownership), as a percentage of the sum of profits from disjoint ownership. The figure shows that while joint ownership results in higher total profits, there are negligible profit losses from disjoint ownership.

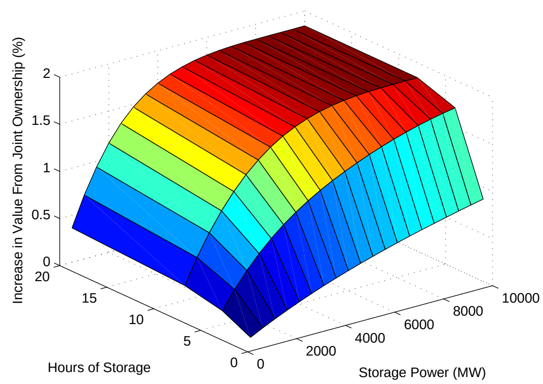

Figure 10: Increase in profits from joint ownership of storage and 10 GW of wind, as a percentage of the sum of profits from individual ownership assuming wind-responsive prices and arbitrage.

Figure 11 demonstrates the benefit to the wind generator of joint ownership by comparing the dispatch of 2 GW of storage with eight hours of storage under the disjoint and joint ownership cases over a sample one-day period.[9] The figure assumes 10 GW of wind are in the system, that storage can be used for arbitrage in both the joint and disjoint cases, and prices will respond to wind generation and storage use. The figure shows that in most hours storage is operated quite similarly, but with joint ownership energy sales from storage are curtailed in some hours (or the storage is charged more than in the disjoint case). Less energy is discharged from storage during these hours in the joint ownership case because the resulting higher energy prices are beneficial to the wind generator, which has high wind availability in these hours. For instance, in hours 2–3, 8–10, and 22–24 some of the available wind energy is put into storage in the joint ownership case (which is reflected by the fact that the storage device is discharged less) so that the remaining wind generation is sold at a higher price. Similarly, in hours 14–20 less energy is discharged from the storage device in the joint ownership case.

The differences in the value and operation of storage under the joint and disjoint ownership cases is reflective of the fact that an independent storage owner will not generally have the same incentives to use storage as the wind generator. However since figure 10 shows relatively small total value differences between the joint and disjoint cases, the value and impacts of storage in the disjoint ownership case will be similar to the joint ownership case. There are differences, however, in the breakdown of these values and impacts. For instance, arbitrage value is slightly higher in the disjoint ownership case than the values shown in figure 9, corresponding to the joint ownership case. These increases in arbitrage value cause some reduction in the external value of storage to the wind generator, as suggested in figure 11. It is important to note, however, that in the disjoint ownership case the storage operator's profits are considerably smaller than the external

[8] In practice, the wind operator's profit-maximization problem is trivial because of the \$19/MWh PTC. The effect of the PTC is that the wind generator is willing to sell in every hour, because the energy price is always greater than -\$19/MWh.

[9] The storage size and day are not chosen for any particular reason. Rather, the figure is intended to be illustrative of the fact that storage use will generally differ between the disjoint and joint ownership cases for all storage sizes.

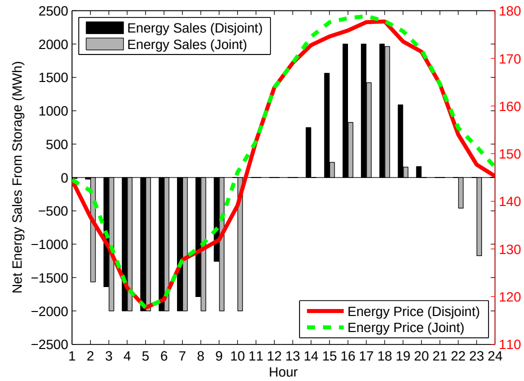

Figure 11: Operation of 2000 MW of storage with eight hours of storage and resulting energy prices under disjoint and joint wind/storage ownership. Figure assumes 10 GW of wind, responsive prices, and arbitrage.

welfare benefit that the storage creates for the wind generator. For instance, the maximum annual value that a disjoint storage operator can earn from energy arbitrage is $17.4 million with 8 GW of storage and 20 hours of storage (more than 8 GW of storage does not provide any added value). By contrast, the use of this storage by the independent storage operator increases the annual profit of a wind generator with 10 GW of wind by close to $28.2 million. Thus, it is apparent that storage is much more valuable to a wind generator than to a merchant storage operator that is using storage solely for arbitrage purposes. This higher value of storage to the wind generator also motivates our studying of storage in the context of joint ownership of wind and storage—since storage is much more valuable to a wind generator, it seems more likely that a wind generator would invest in storage compared to a merchant operator. It is also interesting to note that since more than 8 GW of storage provides no incremental value to the independent storage owner, storage is used inefficiently in the disjoint ownership case from the wind generator's perspective. This is because the wind generator would use and derive value from more than 8 GW of storage, whereas the independent storage operator does not.

6. Conclusions

In this paper we analyze the use of storage as a means to increase the value of wind generation and the profits of a wind generator. We demonstrate that because of the relationship between wind availability and the ability of strategic generators to exercise market power, wind energy will tend to be less valuable on average than the overall value of energy. We also show that as more wind enters the market, the difference between the overall value of energy and wind energy will grow, and the profitability of wind generators will decrease. These effects on the value of wind generation can act to deter wind generators from entering the market.

We show that coupling energy storage with wind generation can increase the selling price of wind and the profits of a wind generator. This increase in the price of wind benefits wind generators and can help to further incent investment in wind capacity. We show, however, that when the profits of conventional generators and consumer costs are taken into consideration, this use of storage reduces social welfare. We also examine the sensitivity of the value of storage to different model assumptions, showing how storage value will vary as a function of storage efficiency, market competitiveness, energy arbitrage, and ownership structure. Table 3 summarizes the effects of these different sensitivities on the value of storage by showing how the year-1 breakeven cost of 500 MW of energy storage with 20 hours of storage varies as a function of the sensitivities that we consider, assuming 10 GW of wind are in the system. It shows that energy arbitrage and disjoint wind/storage ownership[10] will tend to have a much smaller effect on the breakeven

[10] The breakeven cost computed for the disjoint wind/storage ownership case uses the total value of storage to the storage owner and wind generator. If we only consider the value to the storage owner, the breakeven cost is $111/kW.

cost than storage efficiency and market competitiveness. We also show that while the joint and disjoint ownership cases are very similar in terms of total storage and wind profits, a disjoint storage owner would earn significantly less value from storage than a wind generator would, suggesting that a wind generator may be more apt to invest in such technologies.

Table 3: Effect of model assumptions on year-1 breakeven cost of 500 MW of energy storage with 20 hours of storage, assuming 10 GW of wind, responsive prices, and an 11% CCR.

Scenario	Year-1 Breakeven Cost ($/kW)
Base Case	318
70%-Efficient Storage	175
60%-Efficient Storage	90
50%-Efficient Storage	39
Six Strategic Conventional Generators	757
Energy Arbitrage	318
Disjoint Wind/Storage Ownership	258

Despite all of these benefits, however, we find that investment in storage is not economic on the basis of increases in the value of storage with current technology costs. The current cost of PHS is at least twice the cost that can be justified on the basis of a wind generator's profit increase, and other technologies, such as electrochemical energy storage, have significantly higher capital costs. As discussed above, if storage is put to multiple uses by a wind generator, such as reducing transmission capacity requirements, the total value of these uses may justify investment. Moreover, transmission constraints could significantly increase the price-related value of storage for a wind operator, if a wind generator often finds its generation curtailed due to transmission constraints. For example, the PJM market has had many hours in which the locational marginal price at some buses becomes negative due to the effect of a transmission bottleneck on wind generators. Because competing wind generators want to ensure they produce energy to receive the $19/MWh PTC, they often submit negative bids which set the margin when a transmission constraint is binding. In such an instance, energy storage that is co-located with a wind generator could provide significantly more value than what we have estimated. Furthermore, storage investment could be economic if one considers other storage technologies. Heat storage, which we have not considered here, could be used to store energy during the winter when heating demands can be high. While heat storage is less expensive than other pure storage technologies, its use would obviously depend on the power system in question having a district heating scheme, which may not be the case in all systems, and would be limited to times of year during which there are heating loads. Because of these restrictions on heat storage, we have not explicitly considered the technology here, although it may prove to be an economic option in some power systems.

References:

Abbey, C., Joos, G., May/June 2007. Supercapacitor energy storage for wind energy applications. IEEE Transactions on Industry Applications 43, 769–776.

Arsie, I., Marano, V., Rizzo, G., Moran, M., 18 August 2009. Integration of wind turbines with compressed air energy storage. In: Power Control and Optimization: Proceedings of the Second Global Conference on Power Control and Optimization. Vol. 1159. American Institute of Physics, pp. 11–18.

Baldick, R., Hogan, W. W., August 2002. Capacity constrained supply function equilibrium models for electricity markets: Stability, non-decreasing constraints, and function space iterations, uCEI POWER Working Paper PWP-089.

Black, M., Strbac, G., March 2007. Value of bulk energy storage for managing wind power fluctuations. IEEE Transactions on Energy Conversion 22, 197–205.

Bushnell, J., January-February 2003. A Mixed Complementarity Model of Hydrothermal Electricity Competition in the Western United States. Operations Research 51, 80–93.

Cavallo, A. J., May 1995. High-capacity factor wind energy systems. Journal of Solar Energy Engineering 117, 137–143.

Deane, J. P., Ó Gallachóir, B. P., McKeogh, E. J., May 2010. Techno-economic review of existing and new pumped hydro energy storage plant. Renewable and Sustainable Energy Reviews 14, 1293–1302.

DeCarolis, J. F., Keith, D. W., March 2006. The economics of large-scale wind power in a carbon constrained world. Energy Policy 34, 395–410.

DeMeo, E. A., Grant, W., Milligan, M. R., Schuerger, M. J., November-December 2005. Wind plant integration. IEEE Power and Energy Magazine 3, 38–46.

DeMeo, E. A., Jordan, G. A., Kalich, C., King, J., Milligan, M. R., Murley, C., Oakleaf, B., Schuerger, M. J., November-December 2007. Accommodating wind's natural behavior. IEEE Power and Energy Magazine 5, 59–67.

Denholm, P., Kulcinski, G. L., Holloway, T., March 2005. Emissions and energy efficiency assessment of baseload wind energy systems. Environmental Science and Technology 39, 1903–1911.

Denholm, P., Sioshansi, R., August 2009. The value of compressed air energy storage with wind in transmission-constrained electric power systems. Energy Policy 37, 3149–3158.

Eyer, J., Corey, G., February 2010. Energy storage for the electricity grid: Benefits and market potential assessment guide. Tech. Rep. SAND2010-0815, Sandia National Laboratories.

Fourer, R., Gay, D. M., Kernighan, B. W., 2002. AMPL: A Modeling Language for Mathematical Programming, 2nd Edition. Duxbury Press.

García-González, J., de la Muela, R. M. R., Santos, L. M., González, A. M., May 2008. Stochastic joint optimization of wind generation and pumped-storage units in an electricity market. IEEE Transactions on Power Systems 23, 460–468.

Green, R. J., July 2008. Carbon trading or carbon taxes: the impact on generators' risks. The Energy Journal 29, 67–89.

Green, R. J., Newbery, D. M., October 1992. Competition in the british electricity spot market. The Journal of Political Economy 100, 929–953.

Green, R. J., Vasilakos, N., July 2010. Market behaviour with large amounts of intermittent generation. Energy Policy 38, 3211–3220.

Greenblatt, J. B., Succar, S., Denkenberger, D. C., Williams, R. H., Socolow, R. H., March 2007. Baseload wind energy: modeling the competition between gas turbines and compressed air energy storage for supplemental generation. Energy Policy 35, 1474–1492.

Holmberg, P., 2007. Supply function equilibrium with asymmetric capacities and constant marginal costs. The Energy Journal 28, 55–82.

Holmberg, P., November 2009. Numerical calculation of an asymmetric supply function equilibrium with capacity constraints. European Journal of Operational Research 199, 285–295.

Hortaçsu, A., Puller, S. L., Spring 2008. Understanding strategic bidding in multi-unit auctions: A case study of the texas electricity spot market. RAND Journal of Economics 39, 86–114.

Klemperer, P. D., Meyer, M. A., November 1989. Supply function equilibria in oligopoly under uncertainty. Econometrica 56, 1243–1277.

LCRA, August 2003. Study of Electric Transmission in Conjunction with Energy Storage Technology. Lower Colorado River Authority, Austin, Texas, prepared for Texas State Energy Conservation Office.

Paatero, J. V., Lund, P. D., October/December 2005. Effect of energy storage on variations in wind power. Wind Energy 8, 421–441.

Sioshansi, R., April 2010a. Evaluating the impacts of real-time pricing on the cost and value of wind generation. IEEE Transactions on Power Systems 25, 741–748.

Sioshansi, R., 2010b. Welfare impacts of electricity storage and the implications of ownership structure. The Energy Journal 31, 189–214.

Sioshansi, R., Denholm, P., Jenkin, T., Weiss, J., March 2009. Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects. Energy Economics 31, 269–277.

Sioshansi, R., Hurlbut, D., July 2010. Market protocols in ERCOT and their effect on wind generation. Energy Policy 38, 3192–3197.

Sioshansi, R., Oren, S., February 2007. How good are supply function equilibrium models: an empicial analysis of the ERCOT balancing market. Journal of Regulatory Economics 31, 1–35.

Sørensen, B., March 1981. A combined wind and hydro power system. Energy Policy 9, 51–55.

Succar, S., Greenblatt, J. B., Denkenberger, D. C., Williams, R. H., June 4-7 2006. An integrated optimization of large-scale wind with variable rating coupled to compressed air energy storage. In: Windpower 2006. American Wind Energy Association, Pittsburgh, PA.

Succar, S., Williams, R. H., April 2008. Compressed air energy storage theory, resources, and applications for wind power.

Swider, D. J., March 2007. Compressed air energy storage in an electricity system with significant wind power generation. IEEE Transactions on Energy Conversion 22, 95–102.

Twomey, P., Neuhoff, K., July 2010. Wind power and market power in competitive markets. Energy Policy 38, 3198–3210.

Wächter, A., Biegler, L. T., March 2006. On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming. Mathematical Programming 106, 25–57.

Walawalkar, R., Apt, J., Mancini, R., April 2007. Economics of electric energy storage for energy arbitrage and regulation in new york. Energy Policy 35, 2558–2568.