Using Storage to Increase the Market Value of Wind Generation

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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 technologies. This is driven, in part, by the negative correlation between wind availability and loads and market imperfections. We examine the use of energy storage to mitigate this issue 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 and show the sensitivity of this value to a number of parameters including storage device size, storage efficiency, and market competitiveness.

Keywords: Wind generation, energy storage, electricity markets, imperfect competition

1. Introduction

One economic disincentive to investing in wind generation is that the average value of wind energy can be lower than other technologies. This is because real-time wind availability tends to be negatively correlated with load whereas energy prices tend to be positively correlated with load. This issue is further exacerbated with high wind penetrations. Since the exercise of market power by conventional generators is increasing with the demand for conventional generation, the exercise of market power will be highest when wind output is lowest, and vice versa. Green and Vasilakos (2009); Twomey and Neuhoff (2009) both examine this issue in the UK market using supply function equilibrium (SFE) and Cournot models, respectively. Green and Vasilakos (2009) 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 (2009) compare average energy prices of wind and conventional generators, and show an average difference of more than £20/MWh in some instances.

One way that this 'price effect' of wind could be mitigated is by coupling energy storage with wind generation. A wind generator that owns a storage device could shift wind energy from periods with low loads and low energy prices to periods with higher loads and prices. Similarly, wind generation could be shifted away from periods in which high wind availability would suppress energy prices to periods in which less wind energy is available. It bears mentioning that the coupling of wind generation and storage has been studied in other contexts, but that this proposed use of storage to increase the market value of wind energy is novel. Greenblatt et al. (2007); Swider (2007); Black and Strbac (2007); Abbey and Joos (2007); García-González et al. (2008) examine the value of using energy storage to manage the variable and unpredictable nature of wind availability in power systems. Most of this analysis has focused on more 'engineering' aspects of wind integration such as grid stability, load-balance, and system security. This analysis has shown benefits from using energy storage as an alternative to other dispatchable generators as a means of managing wind variability. Cavallo (1995); LCRA (2003); Denholm et al. (2005); DeCarolis and Keith (2006);

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Succar et al. (2006); Greenblatt et al. (2007); Denholm and Sioshansi (2009) consider the use of storage to increase the utilization of transmission assets by wind farms. 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 farm and storage device.

This paper examines the potential benefits that energy storage could provide in increasing the market value of wind generation in the ERCOT (Texas) market. Using a SFE model to represent the bidding behavior of conventional 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 the benefits that coupling a storage device with wind will provide in increasing the value of wind energy and discuss the sensitivity of this value to several of our model assumptions such as market competitiveness and storage device efficiency. We finally show that coupling wind generation with storage in a market in which energy prices respond to wind availability yields a greater combined value than having the assets owned separately. The remainder of this paper is organized as follows: section 2 describes the SFE and storage optimization models and data used in our analysis, section 3 summarizes our results while section 4 discusses their sensitivity to our model assumptions, and section 5 concludes.

2. Model

Our model assumes that the market consists of a set of strategic generators, who optimize their behavior in the market, and a competitive fringe that consists of wind generators and non-strategic conventional generators. The strategic generators are assumed to compete in the market by submitting supply functions, which indicate the quantity of energy they are willing to supply at each given price. Klemperer and Meyer (1989), which first develops the SFE model, assumes firms compete in supply functions because of uncertainty in demand. Green and Newbery (1992) applies the SFE model to the British electricity market and notes 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), which 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 in Klemperer and Meyer (1989). Moreover, because wind availability is uncertain (even hour-ahead), the presence of wind generators will add to the demand uncertainty that the strategic firms face.

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

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

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) gives a set of coupled differential equations characterizing an SFE. Firm i's FONC becomes:

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

As discussed in Klemperer and Meyer (1989), 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 the differential equation becomes:

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

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 (2009) the ERCOT market is modeled based on the generator set, operating costs, and loads from 2005, while wind penetration is scaled up by up to an additional 10 GW above the 2 GW of wind that was operated in 2005. Based on Sioshansi (2010) and empirical evidence in Sioshansi and Oren (2007) 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. The 2 GW of wind that was operating in 2005 is included in the generator portfolios of the firms it was owned by in 2005, whereas the incremental wind is assumed to be owned by a separate entity. Thus, our analysis of wind value focuses on the economic performance of this additional capacity.

Generation costs of conventional generators are computed using engineering estimates, with heat rate and fuel cost data obtained from Ventyx and Platts. Nuclear generators are assumed to be operated as must-run units by the system operator, and not bid strategically by the generators. Real-time wind availability is based on modeled historical mesoscale data for 2005 provided by 3TIER. For wind generators that were operating in 2005, wind availability is based on associating each wind farm with the location in the 3TIER data that is geographically closest and using the modeled data.[1] For the incremental wind generators, we determine the locations based on the sites of planned wind farm installations through 2011 and assume 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 output of the incremental wind farms is scaled based on the assumed capacity. Hourly metered load data, as reported by ERCOT, is combined with the marginal cost functions of the competitive fringe and nuclear output to yield the demand function, $D(p, t)$.

The computed equilibrium supply functions are combined with the actual load and the marginal cost of the competitive fringe to determine a market price function, $p_t(q)$, which gives the price of energy as a function of net energy sold by the incremental wind generator in hour t. For cases in which the wind generator does not own a storage device, the wind generator is assumed to sell its entire output in each hour unless the price of energy goes below the \$19/MWh wind production tax credit for which wind generators are eligible, in which case it would curtail its output. For cases in which the wind generator does own a storage device, we use the model in Denholm and Sioshansi (2009) to maximize combined profits from the wind farm and storage device. In order to give the formulation of the co-optimized model, we first define notation for the the following parameters:[2]

- T: number of hours in planning horizon
- κ: power capacity of storage device (MW)
- h: hours of storage in storage device[3]
- η: roundtrip efficiency of storage device
- 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 of storage device at the end of hour t

[1] Alternatively, actual generation data from 2005 could be used for these wind farms. We opt not to use this approach, because actual generation data is censored due to transmission-related wind curtailments, which, as discussed by Sioshansi and Hurlbut (2009), were non-trivial.

[2] See Sioshansi et al. (2009) for a discussion of modeling storage devices.

[3] 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.

- 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

The formulation of the model is then given as:

$$
\begin{array}{llll}
\max & \displaystyle\sum_{t=1}^{T} p_t(\sigma_t) \cdot \sigma_t + X \cdot w_t & & \\
\text{s.t.} & l_t = l_{t-1} + s_t - d_t & \forall\ t = 1, \ldots, T & \text{// storage level definition} \\
& \sigma_t + s_t - d_t/\eta = w_t & \forall\ t = 1, \ldots, T & \text{// energy balance} \\
& w_t \leq \bar{w}_t & \forall\ t = 1, \ldots, T & \text{// wind capacity} \\
& s_t \leq \kappa & \forall\ t = 1, \ldots, T & \text{// storage power capacity} \\
& d_t \leq \eta\kappa & \forall\ t = 1, \ldots, T & \text{// discharge power capacity} \\
& l_t \leq h\kappa & \forall\ t = 1, \ldots, T & \text{// storage energy capacity} \\
& l_t, s_t, d_t, w_t \geq 0 & \forall\ t = 1, \ldots, T & \text{// non-negativity}
\end{array}
$$

In the combined wind/storage case, we assume the wind generator optimizes the dispatch of its storage device over the year one day at a time, using a rolling two-day planning horizon. As discussed in Sioshansi et al. (2009), the two-day planning horizon is used to ensure that the storage device is not fully discharged at the end of each day, which would be optimal behavior if a one-day planning horizon is used. We further assume that the wind generator has perfect foresight of wind availability and the market price function.

Because the equilibrium supply functions given by equation 1 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, as demonstrated in figure 1, which shows the approximation to be relatively good. The wind generator's profit-maximization problem is formulated using AMPL 11.21 and solved using ipopt 3.5.4. Because the market price function is assumed to be quadratic, the profit-maximization problem will be non-linear and non-convex. As such, our estimates may understate the value of energy storage, since we are not guaranteed to find global optima, and our results should be viewed with this in mind.

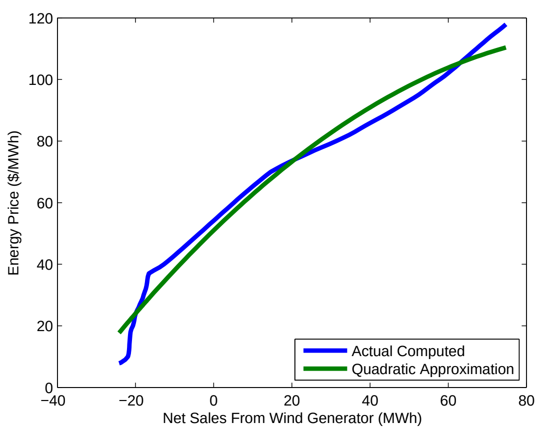

Figure 1: Actual computed market price function and quadratic approximation for 1 January, 2005.

3. Price of Wind and Value of Storage

Table 1 demonstrates the effect of energy prices responding to wind generation by summarizing the effect of the incremental wind generator on the energy-weighted average price of wind generation and the average load price, for the case in which the wind generator does not own a storage device. 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). 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 depresses energy prices—which is shown by a 5.7% decrease in the overall price of energy with 10 GW of added wind. Because the price-depressing effect of wind is concentrated in hours in which there is wind available, the price-suppressing 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 (2009); Twomey and Neuhoff (2009). 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: Energy-weighted average selling price of wind generation and overall price of energy with fixed and wind-responsive prices.

	Wind Capacity (MW)	Wind Price ($/MWh)	Overall Price ($/MWh)
	Fixed Prices	92.48	98.94
Responsive Prices	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

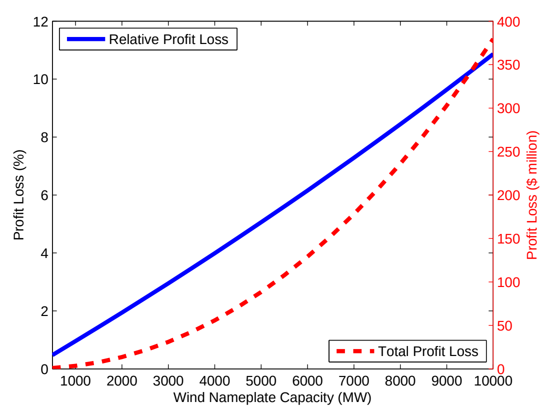

Figure 2: Wind generator's annual profit losses from wind-responsive prices, relative to profits from fixed prices.

Figure 3 summarizes the effect that adding a storage device will have on raising the selling price of wind energy by allowing the wind generator to shift output to higher-priced periods and partially mitigate the price-suppressing effect of wind. The figure assumes a 10 GW wind generator that owns a storage device with a power capacity of between 500 and 10000 MW, between 1 and 20 hours of storage, and a roundtrip device efficiency of 0.8. As Sioshansi et al. (2009) note, depending on the underlying technology storage devices can range between the sizes we consider here. They also note that 0.8 is a reasonable device efficiency, but is at the upper end of storage technologies available today. We consider the effect of device efficiency further in section 4. The figure also assumes a no-arbitrage restriction on the use of the storage device—which restricts the wind generator to use the storage device solely for shifting of wind generation between periods. This constraint is imposed in the wind generator's profit-maximization problem by adding the constraint:

$$s_t \leq \bar{w}_t \quad \forall\, t = 1, \ldots, T.$$

We impose this constraint because we are interested in the use of storage to increase the value of wind generation and not on the value of arbitrage (we do, however, relax this constraint in the sensitivity analysis in section 4 to capture the added value of arbitrage).

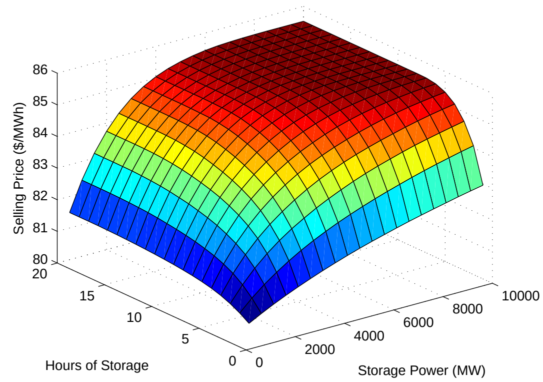

Figure 3: Average selling price of generation from a 10 GW wind operator with storage assuming wind-responsive prices and no arbitrage.

The figure shows that energy storage can play a noticeable role in increasing the market price of wind generation. The smallest-size storage device that we consider, a 500 MW device 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 from energy sales. The largest device, a 10 GW device 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 selling price of wind generation reaches a saturation frontier, which is roughly in the shape of a parabola going through device 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 the resulting profits are increased with device sizes above this parabola, the incremental increases are small compared to the gains from smaller device sizes.

Figure 4 summarizes the resulting effect of an eight-hour 500 MW storage device on the profits of the wind operator, assuming the no-arbitrage restriction is still in place. The value of the storage device, which is defined as the increase in the profits of the wind generator from owning the storage device, 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 farm shows that the wind generator does not 'saturate' the ability of the storage device to provide value. Moreover, the figure shows that for smaller-sized wind farms, the increase in profits from generation shifting outweighs the profit loss from wind-responsive prices.

Figure 5 summarizes the value of storage for a 10 GW wind operator with the same no-arbitrage condition, showing a similar plateauing to that seen in figure 3. One natural question that arises from this analysis is what size storage device can be justified based on the increase in the wind generator's profits. This type of analysis would require comparing the capital cost of the storage device to several year's worth of

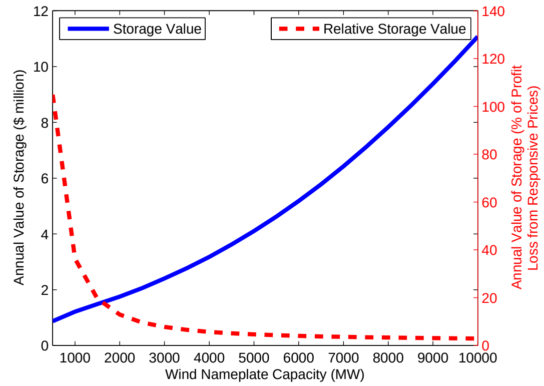

Figure 4: Annual value of a 500 MW storage device with eight hours of storage assuming wind-responsive prices and no arbitrage.

revenue streams from the storage device. In lieu of making assumptions about future market and wind conditions, we opt to present a year-1 breakeven cost assuming an 11% capital charge rate (CCR), which is meant to capture all of the various financing parameters (cf. Denholm and Sioshansi (2009)). Using this CCR, the breakeven cost of the storage device is increased by roughly a factor of nine above the annual value of the storage device given in figure 5. Although the resulting breakeven cost is below the cost of most modern storage technologies—the highest breakeven cost for the 10 GW wind operator is \$317/kW, whereas Denholm and Sioshansi (2009) use a cost estimate of \$750/kW for a compressed air energy storage system (CAES)[4]—a storage system may be economic if it is intended for multiple uses, such as reducing the transmission capacity requirements and shifting generation to higher-priced hours. On the other hand, these multiple uses of the storage device 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.

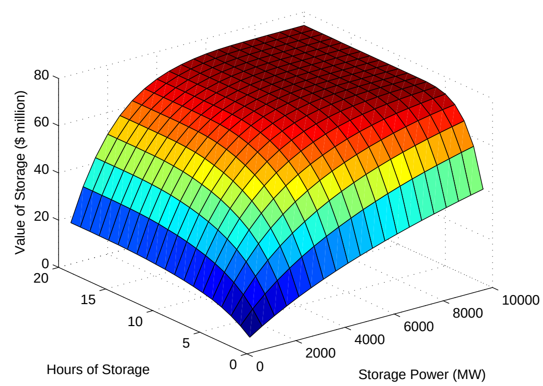

Figure 5: Annual value of storage owned by a 10 GW wind operator assuming wind-responsive prices and no arbitrage.

4. 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 the efficiency of the storage device, the competitiveness

[4]It bears mentioning that because CAES is a hybrid storage device that uses natural gas when discharging stored energy, it is not directly analogous to the analysis we have done here. Nevertheless, we use the cost of CAES as a benchmark because CAES has one of the lowest capital costs of storage technologies presently available.

of the market, and the ability of the wind generator to use the storage device for arbitrage.

Figure 6 summarizes the effect of the efficiency of the storage device on its value, by comparing the value of lower-efficiency devices to an 80%-efficient device. The loss in value is given as a percentage of the value of the 80%-efficient device, and assumes the wind generator has a 10 GW wind farm and that the device has four hours of storage. 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 39.2%. This sensitivity to the efficiency of the device is also observed in 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. As Sioshansi et al. (2009) note, an efficiency of 80% is towards the upper-end of modern storage devices, with pumped hydroelectric systems having efficiencies in the range of 65-85% and large battery systems having efficiencies of around 65-75%.

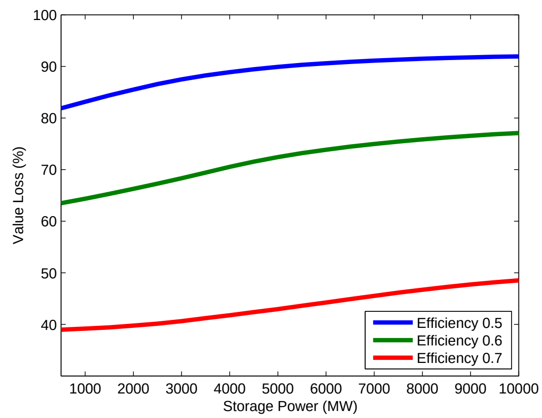

Figure 6: Loss in value of lower-efficiency storage device as compared to an 80%-efficient device assuming 10 GW of wind, four hours of storage, wind-responsive prices, and no arbitrage.

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 firms (because $\hat{n}$ is computed based on the actual market shares of the two firms, our analysis has used $\hat{n} = 1.97$), which will result in abundant 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 generating loads are high, which will also tend to be periods in which wind availability is low. In a more competitive setting, by contrast, market prices will be closer to marginal cost, even when loads are high.

We repeat our analysis for a case in which the market has six symmetric strategic firms. We derive the cost functions of the strategic firms from the same cost estimates for TXU and Texas Genco (i.e. we use the same cost function for the strategic firms in this case as in the duopoly case), and use the same demand function estimate, but assume that $\hat{n} = 6$ in deriving the SFE. Figure 7 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. The more competitive market tends to suppress prices overall, because the strategic firms have less opportunity to exercise market power, which will tend to reduce the value of wind generation. On the other hand, as shown in figure 8, the value of storage is significantly higher in the more competitive case, because there is added value in the wind generator being able to shift its wind generation to periods with extremely high generating loads, which can significantly increase the market price of its energy. Moreover, comparing figures 7 and 8 to figures 3 and 5 we see that in this more competitive setting, the value of storage for the device sizes we have considered does not plateau. It is also interesting to note that in this more competitive case, the year-1 breakeven cost of a 500 MW 20-hour storage device is \$756.74/kW, which could make investment in a CAES device by a wind operator an economic decision, assuming the \$750/kW cost used in Denholm and Sioshansi (2009).

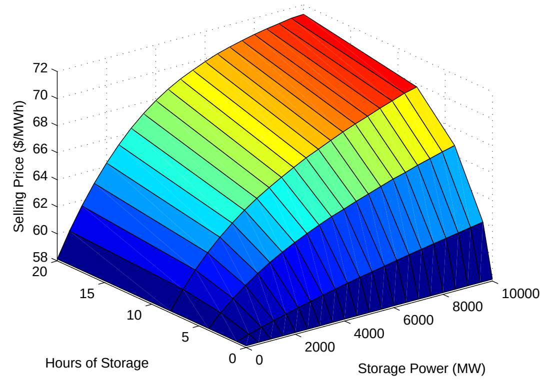

Figure 7: Average selling price of generation from a 10 GW wind operator with storage assuming wind-responsive prices, no arbitrage, and six symmetric strategic generating firms in the market.

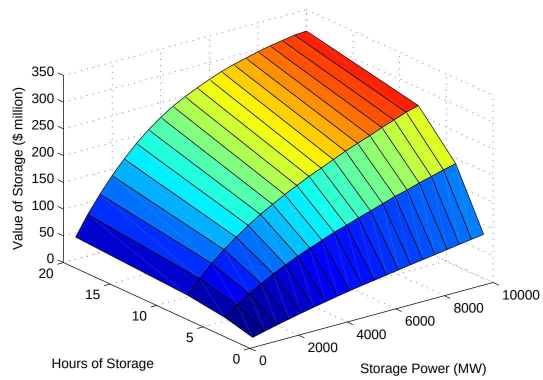

Figure 8: Annual value of storage owned by a 10 GW wind operator assuming wind-responsive prices, no arbitrage, and six symmetric strategic generating firms in the market.

The final sensitivity analysis that we consider is the value of allowing the wind generator to use the storage device both for storage of wind energy and for arbitrage. Figure 9 summarizes the arbitrage value of a storage device owned by a 10 GW wind operator, where the value of arbitrage is defined as the increase in profit when the no-arbitrage constraint 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 wind shifting. 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 may be 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 with interday arbitrage.

Another question raised by the use of storage by a wind generator is whether there are any superadditive profit gains from having the wind generator co-optimize the dispatch of the storage device with the availability of wind, compared to a case in which storage is dispatched independently of wind. Figure 10 summarizes the value of co-optimization of wind and storage by a 10 GW wind generator. The figure shows the increase in profit from joint ownership (above the sum of profits from independent operation of the wind and storage), as a percentage of the sum of profits from independent operation. The figure shows that there are some relatively modest profit gains from co-optimization.

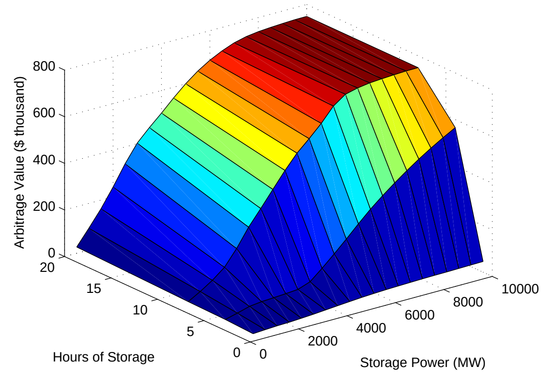

Figure 9: Annual arbitrage value of storage owned by a 10 GW wind operator assuming wind-responsive prices.

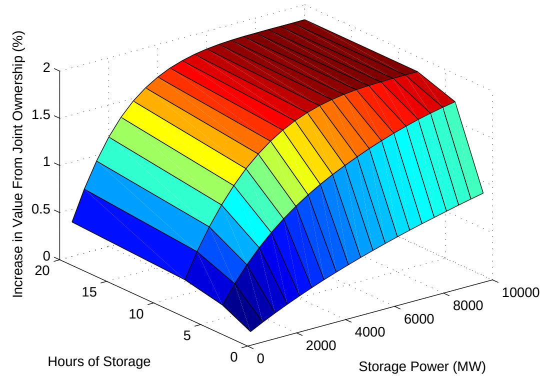

Figure 10: Increase in profits from joint ownership of 10 GW of wind and storage, as a percentage of sum of profits from individual ownership assuming wind-responsive prices and arbitrage.

Figure 11 demonstrates the benefit of joint ownership by comparing the dispatch of an eight-hour 2 GW storage device in the joint storage ownership (JS) and individual storage ownership (IS) cases, assuming a 10 GW wind generator. As the figure shows, the benefit of joint ownership is that in periods of high wind availability the dispatch of the storage device can be tailored to increase the price at which wind generation is sold. 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 difference in the value of storage under the joint and individual storage cases is reflective of the fact that an independent storage owner will not have the same incentives to use storage as the wind generator, however the fact that the profit difference between the two cases is so small suggests that independent storage ownership may closely replicate the joint ownership outcome from a societal standpoint, although the benefits may not be entirely captured by a wind operator (Sioshansi (2010) discusses the issue of ownership structure as it relates to incentives to use storage more generally).

5. Conclusions

In this paper we analyzed the use of storage as a means to increase the value of wind generation and the profits of a wind generator. We demonstrated that because of diurnal load and wind availability patterns and because the ability of strategic generators to exercise market power will be dependent on generating loads and negatively correlated with wind availability, wind energy will tend to be less valuable on average

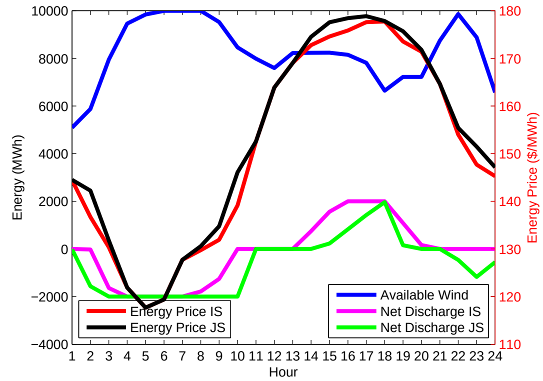

Figure 11: Differences in operation of a 2000 MW storage device with 8 hours of storage under individual storage ownership (IS) and joint storage ownership (JS) by a 10 GW wind operator.

than the overall value of energy. We also demonstrated 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 showed 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 both benefits wind generators (and can help to further incent investment in wind capacity) and increases the social value of wind. The value that storage can provide in this regard will tend to plateau, and there are tradeoffs between the energy and power capacity of the storage device used. As Sioshansi et al. (2009) note, different generating technologies will have different capital costs as a function of the power and energy capacity of the device. We also examined the sensitivity of the value of storage to different assumptions of the model. Importantly, we showed the storage device efficiency and competitiveness of the market will greatly influence the value of storage. Although we did not present a detailed lifetime cash flow analysis, we showed that the year-1 breakeven cost of the storage device is below the capital cost of most storage technologies available today—except in the case of the six-firm market setting. However, if energy storage can be put to multiple uses by a wind generator, such as to reduce transmission capacity requirements and help manage variability in output, the combined value of these uses may make storage an economic option for wind generators with current technology costs.

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