Can a Wind Farm with Storage Survive in the Day-ahead Market?

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Abstract

We investigate the economic viability of coupling a wind farm with compressed air energy storage (CAES) to participate in the day-ahead electricity market. In our analysis we assume that renewable portfolio standards have been fully met and government subsidies have expired. Optimal hourly dispatch quantities of electricity for one year are calculated using a dynamic programming model with the objective of maximizing hourly revenues. Inputs for the model are wholesale electricity prices and wind power forecasts from a single wind farm. Dispatch quantities from the model are then used with measured wind power generation data to determine hourly profits for the wind farm.

We find that annual revenue for the wind farm would not be enough to cover annualized capital costs of the wind farm and CAES facility when using market prices for Texas and Iowa during the years 2006 to 2009. We then estimate market prices with a carbon price of \$20 and \$50 per tonne CO_2 and find that revenue would still not cover the capital costs. The implied cost per tonne of avoided CO_2 for a profitable wind – CAES system is roughly \$100, with large variability due to electric power prices.

1. Introduction

Wind energy in the Unites States has experienced rapid growth as a result of aggressive energy policies at multiple levels of government. In thirty-one U.S. states, renewable portfolio standards (RPS) place mandates on the amount of electricity production from renewable resources (DSIRE, 2010). RPS mandates and penalties for non-compliance vary from state to state, but all are designed to increase the amount of renewable energy used to meet electricity demand (Wiser and Barbose, 2008). Additionally, many states offer tax incentives for renewable energy such as accelerated depreciation and reduced or waived property taxes (DSIRE, 2010).

At the federal government level, the primary incentive for electricity production from renewable energy sources is the production tax credit (PTC). For each unit of energy produced from renewable energy, the generator receives a tax credit during the first ten years of generation. Originally established in the Energy Policy Act of 1992, the PTC has been renewed every few years up to the present. It has been allowed to expire three times, creating a one year gap in the subsidy, before being renewed. The current version of the PTC ($21/MWh) is scheduled to end in 2012.

Wind energy accounts for the largest single share of non-hydroelectric renewable energy throughout the U.S. (Wiser and Bolinger, 2010). Wind power is expected to play a large role in future electricity generation in order to meet the Department of Energy's renewable power goal of twenty percent by 2020

(Logan et al., 2009). As wind energy continues to provide a larger portion of the electricity generated in the U.S. and Europe, grid stability will become an important issue. Unforeseen drops or increases in wind generation must be balanced in real time with fast ramping generation such as natural gas or hydro power plants.

Most wind generation in the U.S. is sold through long term power purchase agreements (PPA) that pay a fixed, per-unit price for all electricity produced over a 15 to 25 year period (Harper et al., 2007; Windustry, 2010). Some wind farms sell electricity on the spot market (Wiser and Bolinger, 2010). PPAs guarantee that all energy will be sold, and remove the risk of price fluctuations inherent in power markets. Utilities benefit by securing renewable energy requirements for RPS mandates. This arrangement essentially means wind generation is treated as "must run" except for times when grid stability is at risk or transmission is constrained. In contrast, conventional generators sell production to the centralized markets at prices that fluctuate according to demand.

Electricity markets balance supply and demand in the power grid. Multiple markets coexist to ensure smooth operation of the electricity grid. Most of the electricity sold in power markets is via the day-ahead market where electricity generation companies submit hourly or sub-hourly bids for contracts one day in advance. Market operators employ economic dispatch algorithms to match bids with forecasted demand and determine generator schedules throughout the following day. Once the day-ahead market is cleared, prices and generation schedules become known and are communicated to generators.

Where wind is currently sold in wholesale markets, it is at a profit disadvantage, since wholesale electricity prices tend to be low at night when most of the wind energy is generated. Additional revenue from the PTC and selling renewable energy credits (RECs), an RPS compliance mechanism, partially offset that disadvantage.

The growth of wind energy has spurred interest in coupling wind farms with energy storage in order to alleviate these problems to some extent and allow wind farms to readily participate in the day-ahead market. The main benefit would be better use of wind energy in the grid. Grid managers use wind forecasts when determining how much electricity is required from conventional generators to meet demand. When forecasts over-predict wind power, reserve generation is used to meet demand. If forecast are too low, generation is reduced from operating units. Energy storage could enhance wind energy by allowing limited control of dispatch from a wind farm and smoothing fluctuations in wind generation. This would allow less reliance on expensive reserve generation for balancing wind forecast errors. It also shifts risk from grid managers to the wind farm operators who profit from the electricity they sell.

During hours when more energy is generated than committed, the excess energy can be stored and used later when committed energy exceeds generation. Storage not only allows a wind farm to provide steady power up to the rated output of the storage system, it also reduces risk inherent in scheduling future energy commitments with uncertain forecasts. Additionally, storage allows a wind farm to dispatch a greater share of generation during periods of peak market prices.

Here we analyze the economic viability of selling wind energy on the day-ahead market when energy storage is possible. We created a model to calculate revenue-maximizing electricity dispatch quantities to offer on the day-ahead market. The model determined dispatch quantities that maximized expected revenue in the day-ahead market given the uncertainty of wind power forecasts (derived from forecast and power output data from a large wind farm). Dispatch quantities from the model were then used with actual wind power data to determine the revenue realized from optimal dispatch. Finally, the revenue was compared with cost estimates to determine economic viability.

If the portion of electricity produced from renewable sources increases beyond the RPS mandate, wind farms will be compelled to sell electrical energy they produce via the electricity markets. This is the case examined here. We assume that the RPS constraint no longer binds and that the wind farm derives no revenue from RECs. We also assume that production tax credits have expired and are not applicable. One case study will not provide definitive results for all wind farms, but it will provide insight into the problem of using energy storage to encourage further wind energy growth.

Previous work by Garcia-Gonzalez et al (2008), Castronuovo and Lopes (2004) and Greiner et al. (2009) proposed models to determine optimal dispatch schedules for a wind farm with energy storage participating in the day-ahead market. In each model, the stochastic problem was solved by averaging deterministic results obtained from a set of possible wind generation profiles. We take an approach similar to Kim and Powell (2009) by creating an optimization model based on dynamic programming. In this algorithm, optimal dispatch quantities are calculated for each hour based on the expected state of the energy storage system and wind forecast at that particular hour. Our model differs from Kim and Powell in three ways (1) we do not assume a probability distribution for wind generation, but rather use real wind data; (2) electricity is not sold in the regulation market; and (3) available stored energy each hour is limited by the power output of the storage facility. In order to characterize wind forecast uncertainty, we use historical data from a wind farm to create empirical probability distributions of the wind forecast errors.

In summary, we present a model to determine revenue-optimal dispatch quantities for the day-ahead market and then use those dispatch quantities with actual wind generation values and market prices to determine annual income for a wind farm with storage. Using optimal dispatch quantities to determine profits is our method of determining the value of a wind farm with storage when the RPS and PTC do not apply. Wind farm valuation is typically done by assuming a capacity factor to determine annual generation and multiplying by a constant price. When the wind farm is not shielded from electricity price fluctuations, the traditional way of determining wind farm value is not applicable. One must consider fluctuating market prices and generation.

This paper is organized into 4 sections. Section 2 describes the model used to determine the hourly dispatch quantities one day in advance along with annual revenue. Results from the model are presented in Section 3. Finally, conclusions are presented in Section 4.

2 Model

2.1 Storage

Large scale energy storage exists in many forms including pumped hydroelectric, compressed air energy storage (CAES), batteries and flywheels. Currently, the least expensive options are pumped hydro and CAES. Nearly 21 gigawatts (GW) of pumped hydro storage exist in U.S. grids (EIA, 2010a), but only two CAES facilities exist worldwide, with several in the development stage (Succar, 2011).

Due to the low capital costs and flexibility in location, we chose CAES as the energy storage technology to use in our model. However, this method is generally applicable to any utility-scale storage. CAES facilities store energy in the form of compressed air in underground caverns. A compressor pushes air into the cavern during the charging process. Air is allowed to escape through an expander and natural gas turbine when the stored energy is used to generate electricity. In stand-alone natural gas turbines, half of the energy contained in the gas is used to compress the air prior to combustion. A CAES facility connected to a wind farm uses electricity generated from wind energy to compress air resulting in a heat rate that is roughly half of that compared to stand-alone gas turbines (Succar, 2011).

Round-trip efficiency is an important parameter used in quantifying an energy storage system. However, due to the additional energy input (gas combustion) into this energy storage system, a round-trip efficiency calculation is misleading. Excluding the energy from combustion, the round-trip efficiency is on the order of 50 percent. With the additional energy input, however, more energy can be removed from a CAES facility than that required to charge it. For every 1 MWh of energy stored in a CAES facility, roughly 1.35 MWh of energy can be supplied (Succar, 2011).

2.2 Wind Forecasts

Participation in the day-ahead market for wind farms requires good wind forecasts. In most markets, hourly dispatch quantities are submitted for the next day. While dispatch quantities need to be calculated for a twenty-four hour period, a wind farm will use longer forecast look-ahead times to optimally manage energy storage levels over a multi day period. Our forecast data had look-ahead times of up to 84 hours. Our model uses forty-eight hours of prediction values to make dispatch decisions for a twenty-four hour period. Since day-ahead markets normally close approximately twelve hours prior to dispatch, there is a time delay between the forecast creation and the first hour of dispatch. Therefore, the forecast must include wind power predictions for time periods beginning twelve hours from the present and ending sixty hours from the present. Figure 1 illustrates the timeline for day-ahead dispatch used in the model described later.

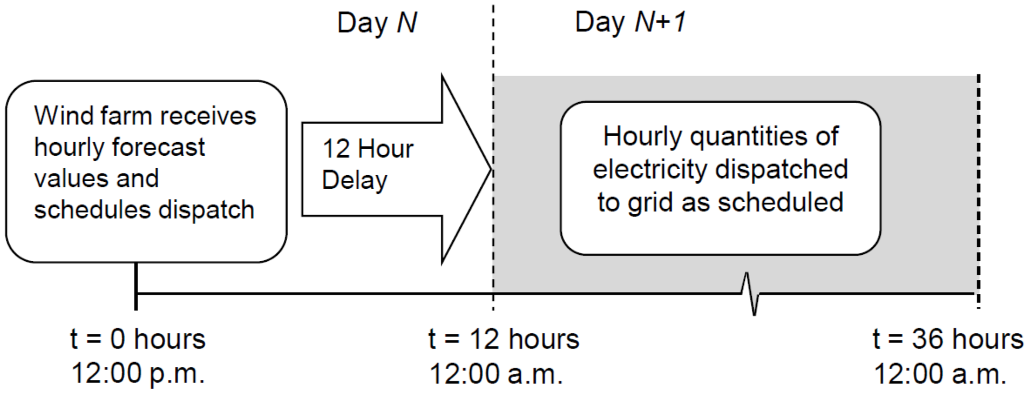

Figure 1: Timeline for participation in the day-ahead market. The market closes at 12:00 pm each day. Dispatch offers are submitted for each hour of the following day.

2.3 Wind and CAES Model

We investigate a hypothetical scenario: a wind farm sells energy on the day-ahead market with no assistance from government subsidies or an RPS; total wind capacity has exceeded RPS mandates and the PTC has been allowed to expire.

A wind farm operator in this situation will determine optimal hourly energy commitments which maximize the wind farm's hourly revenue. Hourly revenue is defined as hourly income from energy sold to the market less the cost of using energy from CAES. We assume a constant marginal cost of energy from the

CAES. Annual profits are the cumulative hourly revenue over one year less the annualized capital costs. Additional assumptions used in the model include: (1) the wind farm is a price taker, (2) all electricity offered to the day-ahead market is accepted for dispatch, and (3) transmission is not constrained.

Dispatch quantities are determined before wind generation and market prices become known. As stated above, wind forecasts are integral in scheduling dispatch. In order to properly use the forecasts, uncertainty associated with the point values of the forecast must be accounted for in dispatch decisions. This is explained in detail in Section 2.7. Price uncertainty is not included in this model. We assume perfect price knowledge each day when dispatch schedules are calculated. In reality, uncertain price forecasts are used to schedule generation. Assuming perfect price knowledge provides an upper bound for the annual revenue results from the model.

Parameters used for the wind farm and CAES facility are shown in Table 1. Due to the desire of the wind farm that supplied forecast and actual power production data to remain anonymous, we will not mention details about the farm beyond the capacity factor and that it is a large installation in a good onshore wind area of the U.S. We set the CAES expander power output power close to the wind farm capacity as a base case scenario. Ramp-up time of the CAES system is not considered in this model. Sensitivity analysis on the base case parameters is presented in Section 3.

Table 1: Parameters for Wind Farm with Storage Used in Optimization Model

Wind Power Capacity Factor	0.28
Wind Generation per Installed MW of Capacity	2445 MWh
CAES expander capacity to wind farm capacity ratio	0.9
Expander to compressor power ratio	1
Storage Capacity	15 hrs
Heat Rate	3500 – 4500 Btu/MWh
Variable Cost of Storage	\$2.5 – \$3.5/MWh
Natural Gas Cost	\$4 - \$7/ 1000 cu ft

Using the range of values for the CAES heat rate, natural gas price and variable CAES operation cost, we calculated a range of possible marginal costs of using stored energy from the CAES facility. From the ranges shown in Table 1, we calculated the base case, low and high values shown in Table 2.

Table 2: Marginal cost values for energy used from the CAES facility

	Low Value	Base Case	High Value
Marginal Cost of CAES energy	\$16/MWh	\$24/MWh	\$34/MWh

The wind farm hourly optimal dispatch quantities for the day-ahead market were computed with a dynamic programming model. For each hour of the day-ahead market there are two decision variables, (1) the amount of energy to place or remove from CAES and (2) the amount of energy to sell. The objective function used in the model is maximizing hourly revenue from day-ahead market electricity sales. Constraints and exogenous variables are explained in the next sections. Dispatch schedules are based on wind power forecasts. Uncertainty of wind generation was modeled with empirical probability distributions created from nearly one year of wind forecast and generation data. Resulting dispatch quantities were then used with actual wind generation data to determine actual revenue gained from the dispatch quantities. This process was repeated for a period of 325 days (due to gaps in the wind generation and forecast data, data from 365 days was not available). Using the dispatch values along with actual wind generation data, hourly revenue and actual storage levels were determined for each day. Figure 2 illustrates the full process to calculate annual revenue.

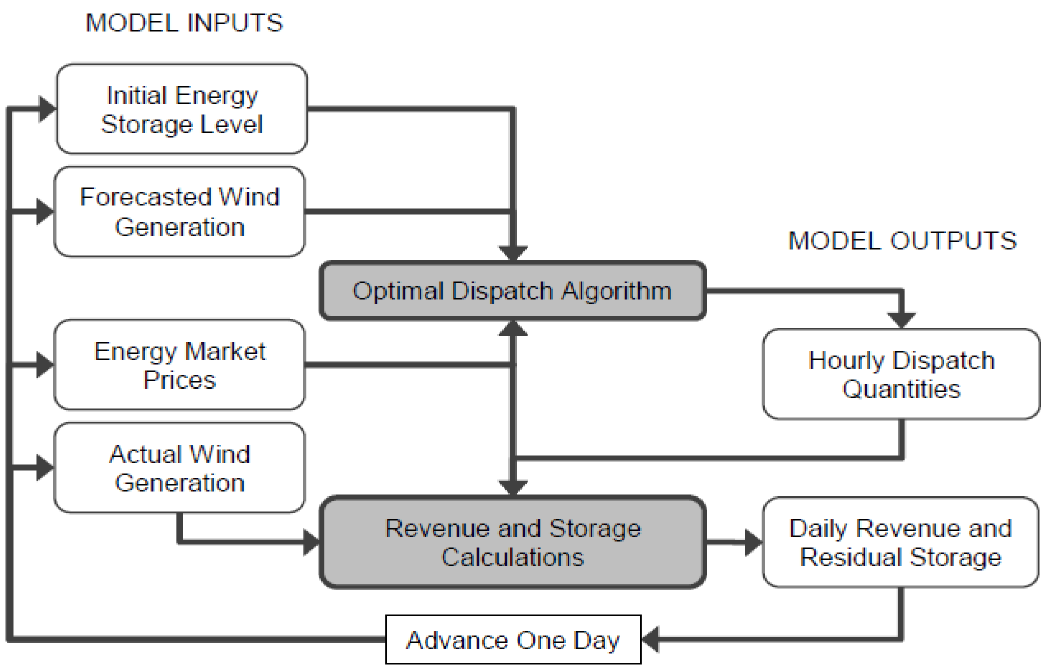

Figure 2: Revenue-optimal dispatch quantities are calculated with forecasted wind generation and energy market prices. The resulting hourly dispatch quantities are the used with actual wind generation to determine the daily revenue and the actual storage level remaining at the end of each day.

2.4 Optimal Dispatch

When storage is available, a wind energy provider will offer energy in the market according to a schedule that maximizes profits. As stated earlier, our model maximizes profits by maximizing revenue. The objective of optimizing revenue over *T* periods is given by

$$\max_{\{Q_t, S_t\}} \sum_{t=1}^{T} R_t(Q_t, S_t) \tag{1}$$

Hourly revenue is given by R_t and is a function of the hourly energy storage levels, S_t, and hourly energy dispatch quantities, Q_t. The optimal set of hourly dispatch quantities and energy storage levels to maximize revenue in the day-ahead market is found with a dynamic programming algorithm. We used optimal dispatch quantities for a twenty-four hour period to simulate offers in the day-ahead market. Equation 1 was solved for a forty-eight hour horizon in order to allow optimal management of the energy storage for the dispatch day while considering trading for the next day. This was done for each day of a year.

Energy dispatch from an intermittent source with limited storage ability is similar to the classic inventory problem studied extensively in the operations research community (e.g. Hillier and Lieberman, 2001). We treat supply as uncontrollable and stochastic rather than their treatment of demand. Dynamic programming is well suited to multistage processes such as energy dispatch from storage. Equation 1 is solved in a backward recursive manner in which decisions for the last time step are optimized first and the solution progresses to the first time interval. The optimal storage transition at time *t* is computed with regards to all remaining time intervals. For each possible energy storage transition, the dispatch quantity maximizing hourly revenue along with the highest expected revenue is computed.

In order to apply dynamic programming, the system is described by a state variable. In this case, the energy storage level is the natural choice. As the solution progresses backwards in time, the optimal path for the current time interval is computed for all possible storage levels. At each stage in the process, expected profit was computed as discussed below. Uncertainty of energy supply was modeled with empirical wind generation probability distributions. Optimizing dispatch in this manner is referred to as explicit stochastic dynamic programming by Nandalal and Bogardi (2007).

An illustration of the optimal dispatch algorithm is shown in Figure 3 with the first and last three hours visible and quantities of energy in storage shown for each hour of the optimization horizon. If energy from wind generation is stored during a particular hour, then the storage level will increase. A decrease in the storage level indicates energy has been removed from storage to be dispatched. Three possible paths for the energy storage level are shown in the diagram. Many potential paths exist from hour 1 to hour 48; our algorithm to determine optimal dispatch seeks the path that produces the greatest revenue. Initially, there is some given level of energy in the CAES. All paths of energy storage levels through the horizon must start at the initial energy level. In order to optimally use energy storage, no excess energy should remain at the end of the horizon.

Therefore, all possible paths end at the minimum storage level.

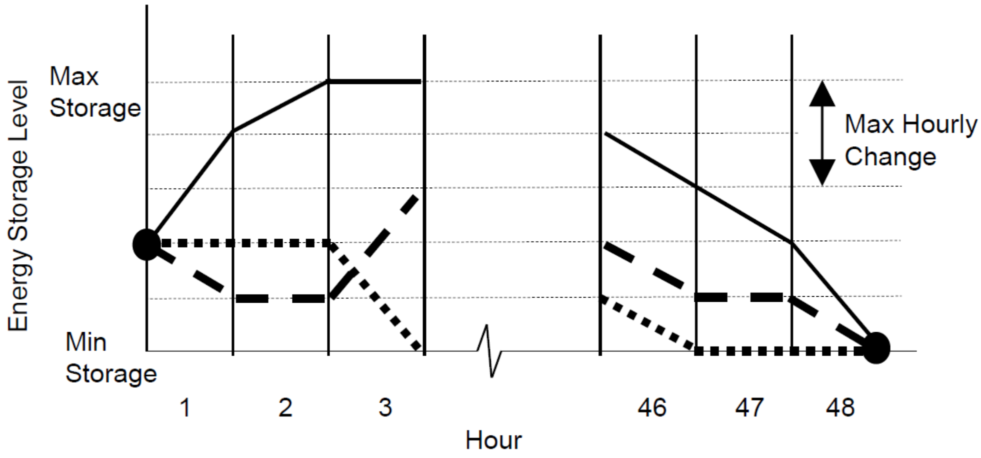

Figure 3: Illustration of potential energy storage level changes during the optimization horizon.

Three things should be noted in Figure 3. First, this algorithm expresses energy storage levels in discrete quantities. This is necessary in order to analyze a finite number of changes in the amount of stored energy during each hour. Second, the change in stored energy during one hour is limited. In the sample diagram, a change in energy storage cannot be greater than two levels during one hour. For example, if the CAES is fully charged, it cannot use all of the energy contained in the compressed air because the expander can only produce electricity at a rate up to its rated power. Finally, all potential paths have the same known initial and final storage levels. It should also be noted that the optimal path is based on wind forecast data and may not be feasible for the actual wind generation during the day of dispatch.

In our model, the storage level resolution was set so that 300 discrete levels existed between the minimum and maximum storage capacity. During each hour of the optimization horizon, all possible transitions in the energy storage level were investigated. For each transition the dispatch quantity giving the largest expected revenue for the current and all remaining hours is calculated. Once all transitions have been analyzed, the optimal path for the amount of energy stored in the CAES is determined to give the maximum revenue. Figure 4 shows an illustration of five possible transitions in energy storage level from a given state during one hour.

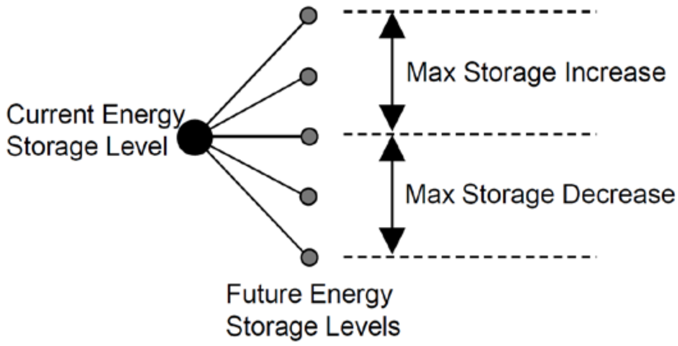

Figure 4: Illustration of five possible energy storage level transitions during one hour for a given current energy level. The limitation to transitions of ± 2 levels represents the CAES ramp rate limitation.

Expanding the marginal revenue function in Equation 1 produces Equation 2. Marginal revenue for each hour denoted by the subscript *t* is calculated as income from electricity sold less the cost of using energy from the CAES.

$$R_t = \begin{cases} Q_t p_t - c_S \hat{s}_t & if\ Q_t \leq \widehat{W}_t + \hat{s}_t \\ (\widehat{W}_t + \hat{s}_t)p_t - \left(Q_t - \left(\widehat{W}_t + \hat{s}_t\right)\right) p_t \alpha - c_S \hat{s}_t & otherwise \end{cases} \quad (2)$$

$$\text{where } \hat{s}_t = \begin{cases} (\Delta S_t)\eta, & if\ energy\ is\ dispatched\ from\ CAES \\ 0, & otherwise \end{cases}$$

Total energy available for dispatch during any given hour is the sum of the estimated wind generation ($\widehat{W}_t$) and the expected amount of energy used from CAES ($\hat{s}_t$) during that hour. When energy is added to the CAES the value for $\hat{s}_t$ is zero since no CAES energy is used for dispatch. Otherwise $\hat{s}_t$ is equal to the decrease in stored energy (ΔS_t) multiplied by the energy input to output ratio (η). The amount of energy taken from the CAES is dependent on the energy storage level transition. However, due to the uncertainty of wind forecasts, the optimal energy storage transitions resulting from the model will not be fully realized during actual dispatch. Therefore, although the amount of energy from CAES is defined each time Equation 2 is used, it is still an estimated value. Wind generation also must be estimated in Equation 2 from the wind power forecasts (see Section 2.7).

When dispatch does not exceed total available energy, revenue is the dispatched quantity (Q_t) multiplied by the market price (p_t) as shown in the first line of Equation 2. The cost of using energy from storage is calculated by multiplying a constant marginal cost (c_S) by the expected amount of energy pulled from storage. If energy is overcommitted, revenue is calculated from the second line in Equation 2 as total available energy ($\widehat{W}_t$+$\hat{s}_t$) multiplied by the market price less the cost of purchasing additional energy in the market to meet the obligation. A weighting factor (α) is also used in the second line of Equation 2 to reduce the occurrence of over-commitments. Offering too much energy on the market can be costly and lead to negative revenue. Therefore, we increased the effect of over commitments on the objective function by using a large weighting factor which improved actual profits.

Determination of energy dispatch and storage take place before wind generation values are known. Therefore, W is a random variable, requiring the optimization problem to be expressed as a stochastic problem that maximizes the expected profits. Expected profit for hour t is determined by averaging over a set of possible wind generation values.

$$E\{R_t \mid \Delta S_t\} = \frac{1}{N} \sum_{g \in G} R_t^g \tag{3}$$

The set of wind generation values (g) contains N possible wind generation values drawn from the set of possible wind generation values (G). The expected revenue for a particular energy level transition is the average value over all N selections of wind generation. For a given energy storage transition (ΔS_t), the expected revenue is concave in dispatch quantity. Figure 5 shows a graph of the expected revenue as a function of dispatch quantity for a given wind forecast and energy storage transition. This shows that optimal dispatch and maximum expected revenue for each possible transition is a straightforward calculation.

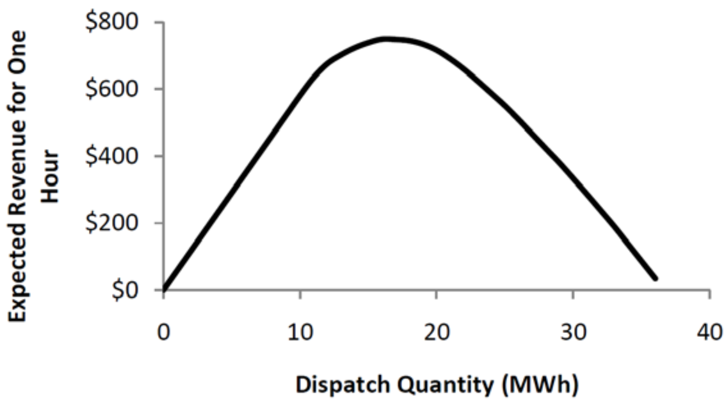

Figure 5: Expected revenue vs. dispatch quantity for one possible storage transition using one hundred possible wind generation values.

The optimization formulation used in this model is expressed fully as

$$\max_{\{Q_t, S_t\}} \sum_{t=1}^{T=24} E[R_t] \tag{4}$$

$$\text{s.t.} \qquad \Delta S^L \leq \Delta S_t \leq \Delta S^U \tag{5}$$

$$\Delta S_t \leq E[W_t] \tag{6}$$

$$0 \leq \mathrm{S_t} \leq \mathrm{S^{max}} \tag{7}$$

$$S_t \leq \sum_{\mathrm{i=1}}^{\mathrm{t}} E[W_i] \tag{8}$$

$$0 \leq Q_t \leq (\Delta S^L + W^U) \tag{9}$$

Accumulation of stored energy during a one-hour interval cannot exceed ΔS^U which is determined by the rated power of the CAES compressor. Alternatively, the maximum drop in stored energy (ΔS^L) is negative and set by the rated power of the expander in the CAES. Constraints (5) and (6) describe limits on the amount of energy transferred to or from the CAES during one hour. Constraint (6) states that an increase in the storage level cannot be greater than the energy produced by the wind farm during the same interval. Constraints (7) and (8) state that the energy storage level cannot exceed the capacity of the CAES and that it cannot exceed the total wind energy produced multiplied by the storage efficiency. Constraint (9) restricts the dispatch quantity to a positive amount less than the sum of the maximum hourly energy discharge and the wind farm capacity, since the largest amount of electricity the wind farm can dispatch is the wind farm capacity plus the output power of the CAES.

2.5 Realized Revenue

Hourly optimal dispatch quantities resulting from the optimal dispatch algorithm in the model are used with actual wind generation values to determine the hourly revenues, over commitments and energy curtailments. In this part of the model, a version of Equation 2 is reused with actual wind generation in place of possible generation values, actual energy from storage in place of estimated energy from storage and a market penalty factor in place of the over commitment weighting factor (Equation 10). The market penalty function was set equal to one in the model, but in reality transaction costs associated with purchasing energy on the real time market makes this larger than one. We show the effect of increasing the market penalty factor in the sensitivity analysis.

$$R_t = \begin{cases} Q_t p_t - c_S s_t & if\ Q_t \leq W_t + s_t \\ (W_t + s_t) p_t - (Q_t - (W_t + s_t)) p_t \varphi - c_S s_t & otherwise \end{cases} \qquad (10)$$

$$\text{where } s_t = \begin{cases} (\Delta S_t)\eta, & if\ energy\ is\ dispatched\ from\ CAES \\ 0, & otherwise \end{cases}$$

Equation 10 is applied to each hour of the year. The realized quantity of energy stored in the CAES is updated after each hour to determine limitations on ΔS_t when determining energy used from CAES. As stated above, the expected amount of energy used from storage is limited by the output power of the CAES and the total amount of stored energy. As long as the energy level of the CAES has not reached its capacity, stored energy accumulates each hour that the committed energy is less than energy generated by the wind farm. While storing energy is not 100 percent efficient, energy output will be greater than energy input due to the natural gas. When the wind farm output is less than the energy committed, energy from storage is used to make up the difference. Energy is curtailed when the difference between wind generation and dispatch is too great to be stored. In similar fashion, energy is over committed when dispatch is too great to be met with available stored energy and wind generation.

In summary, the model maximizes marginal hourly profit for a wind energy provider. The decision variables are the hourly dispatch and storage quantities. Dynamic programming was used to determine the optimal combination of dispatch and storage amounts based on wind forecast data. Optimal dispatch quantities were then used to determine revenue for one year.

2.6 Market Clearing Price Data

In order to create multiple price scenarios, the model was run with price data from the western zone of the ERCOT market in Texas and the Iowa zone of the Midwest ISO (MISO) market. Prices for ERCOT came from the balancing market while MISO prices were from the day-ahead market. ERCOT had no central day-ahead market for the years studied. Model results are used to estimate annual income for a wind farm with CAES so one year of market prices was used for each implementation of the model. For each market used, prices from 2006 to 2009 were used, giving a total of eight results for annual income. Descriptive statistics for each price scenario are shown in Table 3 below.

Table 3: Market price statistics for ERCOT and MISO from 2006 to 2009. All values are in U.S. dollars per megawatt-hour.

	Year	Mean	Std. Dev.	Min	Max
MISO (Iowa Zone)	2009	24.09	21.08	-133.27	284.00
	2008	47.75	37.94	-233.52	449.72
	2007	49.89	28.52	3.23	236.59
	2006	42.72	26.30	2.86	329.51
ERCOT (West zone)	2009	25.89	41.53	-235.38	1664.30
	2008	54.64	84.37	-523.20	2076.30
	2007	52.86	51.67	-407.91	929.99
	2006	51.37	31.91	-209.49	823.75

MISO prices have been less volatile than ERCOT prices, at least partially because balancing market prices were used for the ERCOT scenarios. According to the 2008 ERCOT market report (Potomac Economics, 2009), average balancing market prices differed by only one dollar per megawatt from average forward prices set in bilateral contracts, although the variance was different. Due to depressed demand and low natural gas prices, electricity prices in 2009 were much lower than previous years throughout the U.S. (Wiser and Bolinger, 2010).

2.7 Wind Forecast and Generation Data

Wind forecast and generation data from a single wind farm for all of 2008 and 2009 were used in this study. Forecasts were generated by a commercial forecast provider four times per day with a look-ahead time of eighty-four hours. After removing gaps in the data, over one thousand forecasts remained for 2008.

We created probability distributions for wind forecast errors using the 2008 forecast errors. These distributions were then used to generate possible forecast errors for each forecast value created in 2009. The underlying assumption in this method is that the forecast accuracy did not change a great deal from 2008 to 2009. In reality, forecast accuracy was worse in the first quarter of 2009, but similar for the remainder of the year. The 2009 data contained forecasts for 325 days.

Forecast uncertainty depends on several factors including look-ahead time and the forecast values. As the look-ahead time moves further into the future, uncertainty increases. Common metrics to quantify forecast uncertainty are the mean absolute error (MAE) and root-mean-square-error (RMSE). Figure 6 shows the MAE and RMSE plots for the 2008 wind farm data.

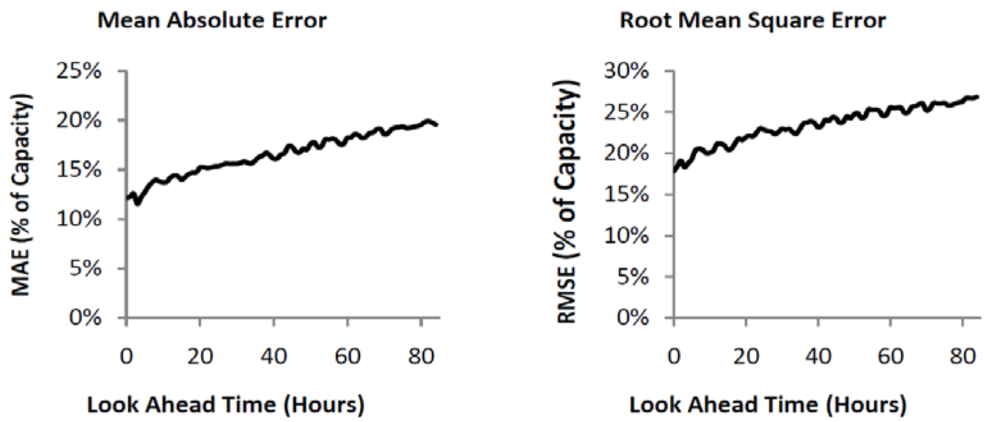

Figure 6: MAE and RMSE graphs for wind power forecasts with an 84 hour look-ahead time. The graphs were made with 2008 data from a single wind farm. Note that all values are normalized by the wind farm capacity.

If a prediction is made near the maximum output of the wind farm, then actual wind generation is more likely to be below the predicted value than above it. Alternatively, for a forecasted value near zero the actual wind generation will likely be above the predicted value. For this reason, treatment of the forecast uncertainty depended on the hour within the forecast horizon and the value of the forecast. We separated the forecast values into eleven power classes for each hour of the forecast time horizon. Figure 7 shows the mean absolute error and RMSE values for each power class eighteen hours after the forecast was made. Uncertainty bars indicate the shape of the two graphs is very similar.

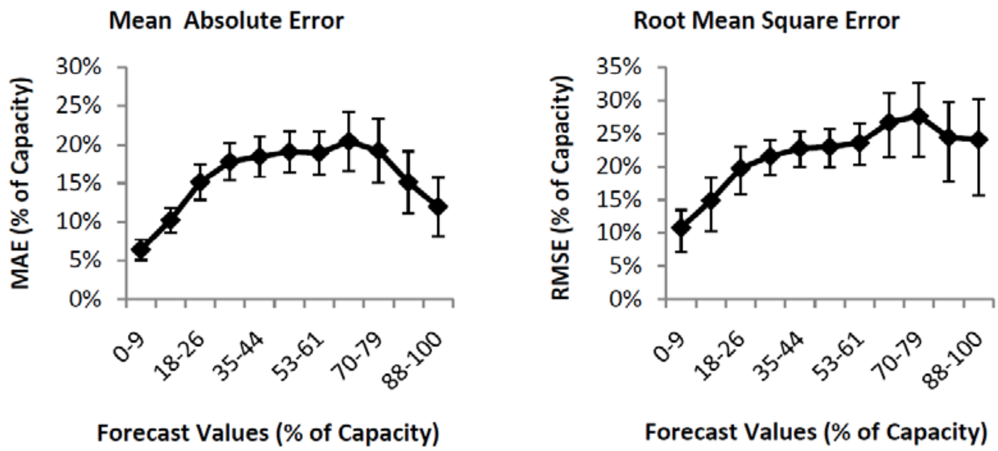

Figure 7: The mean absolute error and root mean square error as a function of forecast power classes eighteen hours after the forecast was taken (six hours into the dispatch schedule) for 2008 for the wind farm used in this study.

Within each power class the forecast error probability distribution function was calculated empirically using 2008 forecast data. This produced a total of 11x48=528 different probability distributions. This method is based on Bludszuweit et al. (2008) who divided forecast values into fifty power classes and fit a beta distribution to the forecast errors within each class. Unfortunately, the fit was not adequate in the tail regions of the distribution. We chose to use empirical distributions of forecast errors for each class of forecast values.

Actual wind generation (*W*) is the sum of the forecasted generation (*F*) and the forecast error (*e*). In order to simulate wind generation, we drew forecast error values from the empirical probability distributions created above and added them to the wind forecast to get simulated wind generation values as shown in Equation 11. Superscripts in Equation 11 denote different possible wind generation values during hour *t*. For each forecast value, we created one hundred possible wind generation values.

$$W_t^i = F + e_t^i \tag{11}$$

3 Results

3.1 Wind and CAES Annual Costs

According to the Windustry website, installed costs for commercial scale wind turbines in 2007 ranged from $1.2 to $2.6 million per MW of capacity (Windustry, 2010). Lawrence Berkley Laboratory found that a sample of 115 wind farms built in 2009 had an average capacity-weighted cost of $2.1 million per MW with the lowest cost $1.3 million per MW (Wiser and Bolinger, 2010). The Energy Information Administration estimates the average wind installation cost at nearly $2 million per MW (EIA, 2010b). Uncertainty of wind farm costs arise due to differences in site requirements such as grid connection fees, equipment transportation, land costs and permit fees. Based on cost numbers in the literature above, we assume a range of installation costs from $1.5 to $2.6 million per MW.

CAES costs are also highly uncertain due to an overall lack of construction experience with CAES plants and differences in sight suitability for a CAES facility. Past cost estimates range from $0.65 - $0.89 million per MW of expander capacity (Denholm and Sioshansi, 2008; Sullivan et al., 2008). Table 4 shows cost estimates used in this study for a wind farm and a CAES facility.

Table 4: Wind and CAES cost estimates

	Capital Cost ($/MW)	Fixed Annual Cost ($/MW)
Wind	1.5 – 2.6 million	25 – 35 thousand
CAES	0.65 – 0.89 million	9 – 12 thousand

Annual costs for a wind farm and CAES facility were calculated for the full range of cost values assuming a blended cost of capital of 6.5%. Based on the values in Table 4, annual costs for a wind farm range from $160 to $270 thousand per MW of installed capacity. Annual costs for the CAES facility range from $67 to $92 thousand per MW of expander capacity. Adding the wind and CAES costs together gives total costs ranging from $220 to $350 thousand per MW of installed wind capacity per year for the wind farm with CAES considered here.

To put these costs into perspective, consider a wind farm with a capacity factor of 0.3. For every MW of installed capacity, the farm will generate 2628 MWh of electricity per year. If all of that electricity is sold at a flat rate of $61 per MWh through a PPA, the wind farm will receive $160 thousand per MW annually. Wiser and Bolinger (2010) calculated the average price of wind power from farms constructed in 2009 to be $61 per MWh (sample size = 130). This does not include the PTC of $21 per MWh or revenue from the sales of renewable energy credits. Once the PTC is included, the revenue increases to $215 thousand per MW of installed capacity, well into the upper half of our estimated annual cost range for a wind farm.

3.2 Annual Profits

Output from the model presented in Section 2 is shown in Figure 8. The graph shows annual revenue for each of the price scenarios considered. Electricity prices were much lower in 2009 than the previous three years which lead to much less revenue for the simulated wind farm. For all years, the average price in the ERCOT market was higher than in the MISO market. Revenue in the ERCOT market was also enhanced by higher volatility that provided an opportunity for a CAES facility to take advantage of highly profitable periods. As Figure 8 shows, annual revenue falls far short of our estimated cost range.

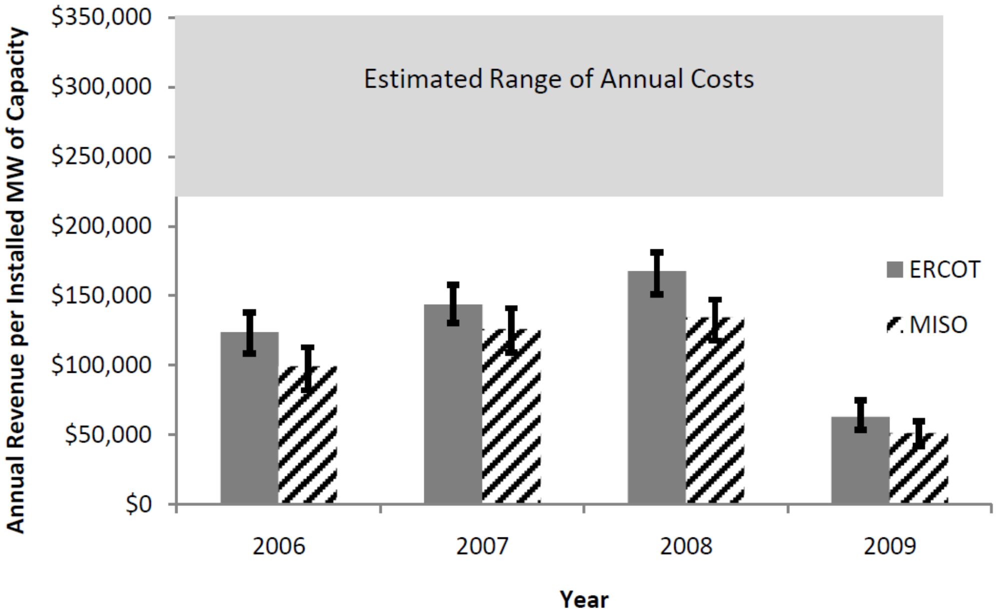

Figure 8: Annual Income for the wind farm with CAES using four different years of price data from the ERCOT and MISO markets. Uncertainty ranges were created by running the model with different assumptions for the marginal cost of stored energy from the CAES facility.

If the wind farm is paid a direct subsidy equal to its annual loss, we can determine the cost of carbon emissions avoided in this situation. The amount of carbon emissions displaced from the wind farm output can be estimated by multiplying the amount of electricity dispatched from the wind and CAES with the average carbon emission factor for the U.S. This amount is then reduced by the amount of carbon dioxide emissions from the CAES to give the net emissions displaced. Using these numbers gives the range of values in Table 5 expressed in dollars per tonne of carbon dioxide emissions avoided.

Table 5: Cost ranges for each tonne of carbon dioxide emissions avoided with the wind farm and CAES.

	MISO	ERCOT
2006	\$100 – 210	\$80 – 190
2007	\$80 – 190	\$60 – 170
2008	\$70 – 120	\$40 – 150
2009	\$130 – 230	\$137 – 251

The storage size used in this simulation provided substantial protection against the curtailment of wind energy. However, the high degree of uncertainty in the wind forecasts prevents the most efficient use of energy storage resulting in significant over commitment of electricity. Figure 9 shows the amount of over commitment for each price input in the model. The vertical axis on the right side of Figure 9 shows the percentage of dispatched energy that was overcommitted.

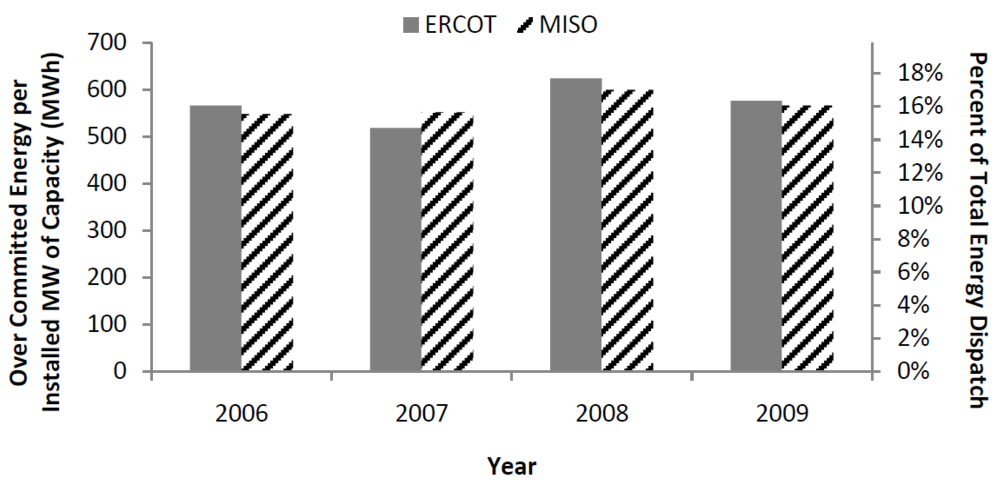

Figure 9: Over committed energy per MW of installed capacity for each of the price scenarios used in the model (base case marginal costs for stored energy).

The model assumes that over committed energy must be purchased from the wholesale market to meet the wind farm's contractual obligation. We assumed that over committed energy is purchased for the day-ahead price. In reality, this energy will be purchased on the real time market for the more volatile spot price. Since the spot price will fluctuate above and below the day-ahead price, over the course of one year using the day-ahead price to purchase over committed energy should be a close approximation to reality. In Section 3.4 we show results when overcommitted energy is purchased for a higher price.

3.3 Annual Revenue with Perfect Forecasts

Since the over committed energy results in revenue loss for the wind farm, wind forecast accuracy directly affects the profits of the wind farm. In order to determine the potential profits from perfect wind forecasts, the model was run using actual wind generation in place of forecasted generation. The value of perfect wind generation information is shown in figure 10, that shows an upper bound to the amount of income the can be obtained with improved forecasting techniques. As indicated in the figure, perfect wind knowledge does not allow the simulated wind farm with CAES to operate with a profit.

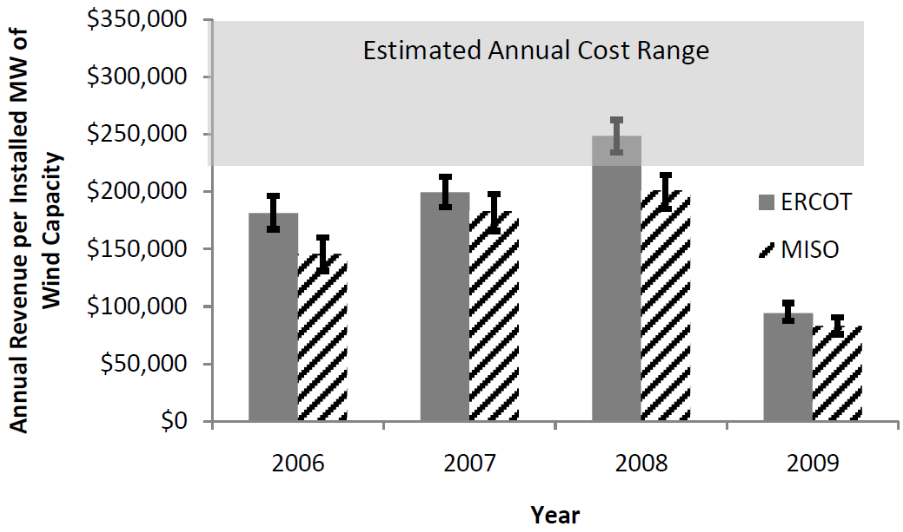

Figure 10: Annual revenue per installed MW of capacity with perfect wind forecasts using four different years of price data from the ERCOT and MISO. Uncertainty bars were created by running the model with different assumptions for the marginal cost of stored energy from the CAES facility.

3.4 Model Sensitivity Analysis

Sensitivity analysis for CAES parameters was carried out to determine how the annual profit is affected by the assumptions made. Since the ERCOT 2008 price scenario provided the largest annual revenue, we used these prices with base case marginal cost assumptions for stored energy to determine how the revenue might change if storage parameters are altered. This was done for storage capacity, CAES power output rating, and CAES compressor power rating. For the base case assumptions with ERCOT 2008 prices, annual revenue was calculated to be $167,000 per MW of installed wind capacity. Sensitivity results are shown in Figure 11.

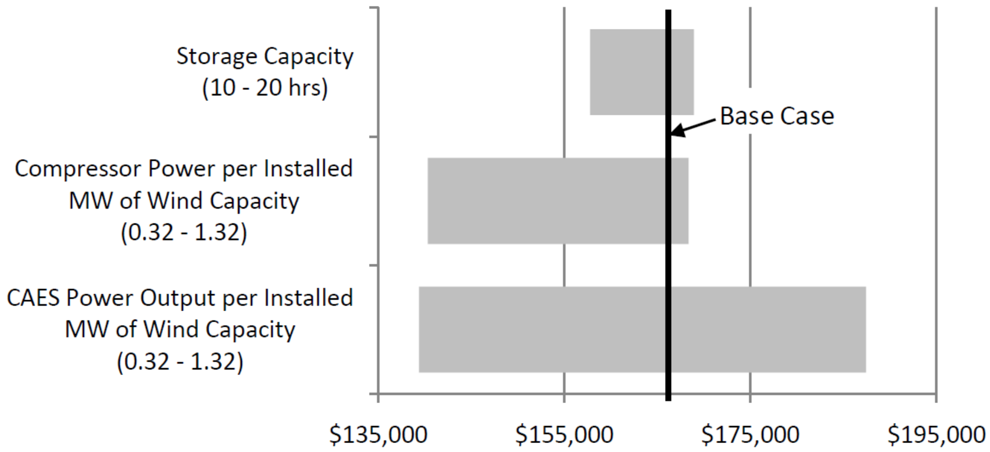

Figure 11: Sensitivity of three selected CAES parameters on the annual revenue results from the model used in this study.

Storage capacity in the model was set to 15 hours. Figure 11 shows how the annual revenue is affected by a range of storage capacity values from 10 to 20 hours. Increasing storage capacity reduces energy curtailment. However, above fifteen hours of storage capacity, most of the curtailed energy is captured. The CAES compressor size determines how quickly energy can be stored. Performing sensitivity analysis on this parameter shows that annual revenue does not increase significantly as the compressor size is increased beyond the base case of 0.9. Noting that the base case output power is 0.9, it seems that a storage charge rate greater that the discharge rate does little for revenue. The most sensitive parameter to the model results is the CAES power output. At the high end of the range, annual profits reach a value of $185 thousand per installed MW of wind capacity when CAES output power is increased by 50%.

The sensitivity analysis shows that annual revenue could be increased slightly if the CAES system output power was increased. In order to consider this option further, one must look at the associated costs. However, even at the high end of the CAES output power range, annual revenue is much lower than annual costs.

We assumed no transaction or penalty costs occurred when additional energy had to be purchased in order to fulfill a day-ahead contract. However, some markets penalize for over commitments and purchasing energy on the real-time market will most likely involve transaction costs. Therefore, we show the sensitivity of our results for the ERCOT 2008 scenario to the penalty factor in Figure 12 below. The loss in revenue from increasing the market penalty factor to 1.1 is roughly 4%. This represents a 10% penalty for over committing energy. At a 1.2 penalty factor the loss is 8%.

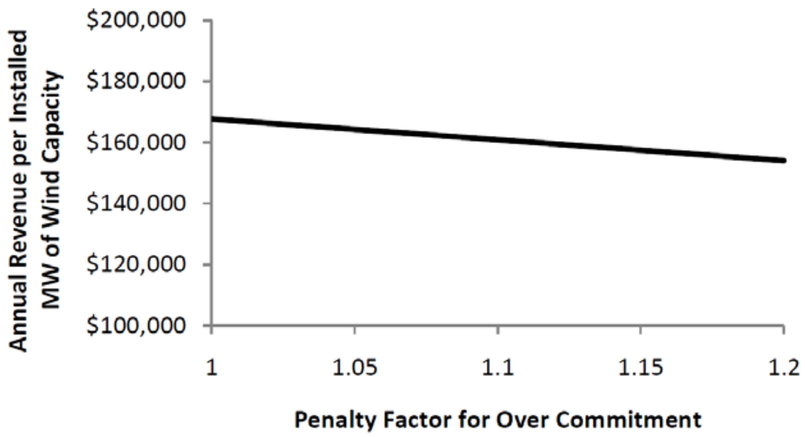

Figure 12: Sensitivity of revenue to the market penalty factor for the ERCOT 2008 price scenario.

3.5 Annual Revenue with a CO_2 Price

If an energy policy is enacted to place a price on carbon dioxide emissions, wind would benefit from higher prices without an increase in generation costs. We ran the model with market prices adjusted to reflect a carbon dioxide price.

The effect of a carbon dioxide price was estimated for the ERCOT region using the method used by Newcomer et al. (2008). First, we obtained generator data from the Environmental Protection Agency's eGrid database (EPA, 2007) to create a short run marginal cost curve. Next, we used ERCOT demand data to estimate market prices. In reality, hourly prices are greatly affected by transmission congestion, generator outages, the volume of electricity sold in the balancing market, and other events. Due to the simplicity of this method, the estimated prices did not match the actual balancing market prices. However, we were able to get estimated average hourly prices close to actual average hourly prices. A second marginal cost curve was created with carbon dioxide prices added to the marginal costs for each generator according to its heat rate and fuel type.

Increased electricity prices will reduce demand. To estimate market prices with a carbon dioxide price, we assumed the price elasticity of demand to be -0.1, the reported typical short term value for elasticity by Spees and Lave (2007). As shown in Newcomer et al. (2008), generator dispatch order in the marginal cost curve will change only slightly for carbon prices up to $50 per ton. To get price inputs for the model in the hypothetical carbon dioxide pricing situation we first subtracted our estimated prices without carbon dioxide pricing from the actual prices. We then added the residuals to our estimated prices in the carbon dioxide pricing scenario. For price spikes greater than the largest generator marginal cost we did not alter the price. The goal was to create market prices resembling a short term reaction to a carbon dioxide price.

Table 6 shows our results for carbon prices of \$20/tonne and \$50/tonne. The EU carbon trading price for the 4th quarter of 2010 was \$21/tonne. A \$20/tonne price on carbon dioxide may be possible with the higher price much less likely in the U.S. Anything beyond a \$50 per ton price on carbon dioxide seems impossible in the near future in the U.S.

Table 6: Annual revenue with ERCOT 2008 prices for three different carbon price scenarios.

Carbon Scenario	Annual Revenue per Installed MW with 2008 ERCOT prices
No CO_2 Price	\$170,000
\$20 per Tonne Price on CO_2	\$190,000
\$50 per Tonne Price on CO_2	\$220,000

Comparing the results shown in Table 5 with costs presented earlier shows that a carbon dioxide price of \$50 per ton would not increase market prices enough to make the wind farm with CAES in our model profitable. ERCOT 2008 prices were much more favorable for the model than the other scenarios tested. It is unlikely that a carbon dioxide price would allow the wind farm with CAES to compete with other generators in the day-ahead market. Our analysis with carbon dioxide prices looked at only the short run price change. In the long run, it is more likely that prices would drop slightly as generation companies adapted to a carbon dioxide price.

We also ran the model with a constant price increase. This is essentially what the production tax credit does for a wind farm. It is not clear how the federal production tax credit would apply to a wind farm with CAES since energy from CAES is not considered renewable. What is clear is that coupling wind farms with storage will not be economically feasible unless wholesale market prices are increased. Therefore, we added \$60 to every hourly price in the price scenarios considered to observe the results. Figure 13 shows the annual revenue for each price scenario along with the estimated annual costs explained earlier. Most of the price scenarios still do not provide enough revenue to justify the investment. Only the ERCOT 2008 price scenario reaches the expected annual cost while four other scenarios climb into the lower range of estimated costs.

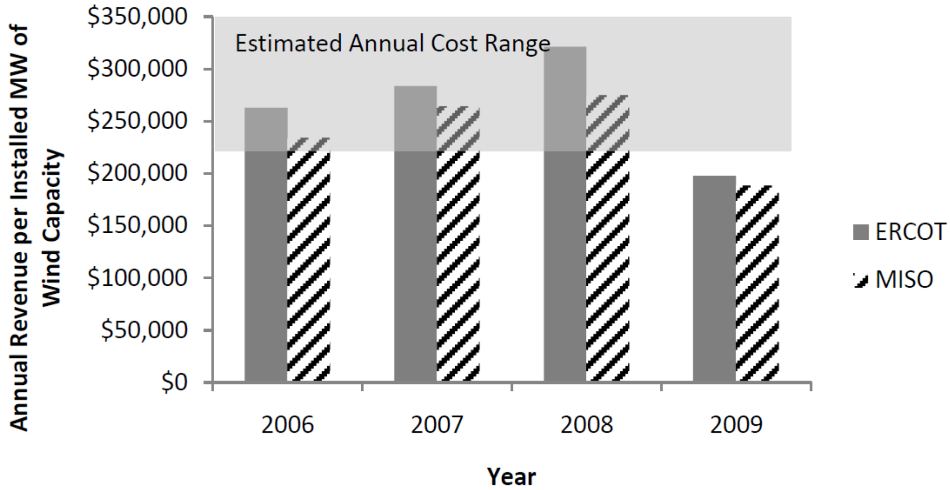

Figure 13: Annual revenue per installed MW of wind capacity with a constant price increase of \$60 per MWh using four different years of price data from the ERCOT and MISO. The estimated annual cost range of the wind farm with CAES is represented in the shaded region.

4 Conclusions and Discussion

We tested the economic viability of a wind farm participating in the day-ahead market with energy storage capability. It is unlikely to be profitable at current electricity prices. This is not a surprising result, as low-carbon wind energy is more expensive than conventional generation. Since the model assumed no transmission constraints or start-up costs for the CAES facility, these results over estimate the revenue potential. If wind penetration continues to grow at a rapid pace, it will affect electricity prices which might make collocating wind with CAES more attractive. It is also possible that a CAES facility would provide more sources of revenue for a wind farm. For example, some markets have a capacity auction for generators in which a CAES facility could compete. It may also be more profitable to sell stored energy from a CAES facility on the regulation market than the day-ahead market.

The benefits from coupling wind with storage must be properly compensated in order to make the economics work from the wind farm's perspective. Forcing wind farms to bid into the day-ahead market and assume all of the risks associated with uncertain wind forecasts allows grid managers the ability to better control intermittent resources such as wind. Our model considered a situation in which wind is treated as any other generator, but environmental benefits of using wind make it much more desirable to many stakeholders than coal or gas generators.

If wind is compelled to bid in the day-ahead markets, collocating wind farms with energy storage may not be the most cost-effective method to achieve this. Energy storage will certainly play a role in future electric grids with large amounts of intermittent generation such as wind or solar. Analysis by Sullivan et al. (2008) indicates that energy storage will allow greater wind capacities in a future grid. This may include centralized or collocated storage facilities. Future energy policies should include energy storage targets to accommodate very large levels of wind penetration. Managing wind resources at current levels is not a problem, but will become more difficult as wind capacity grows. In a carbon constrained world, electricity prices will have to be higher for collocated energy storage to work with wind generation.

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