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Can a wind farm with CAES survive in the day-ahead market?

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HIGHLIGHTS

- ▸ We modeled a wind farm participating in the day-ahead electricity market.
- ▸ We calculated optimal day-ahead market offers based on wind forecasts.
- ▸ Revenue is then calculated using measured wind power.
- ▸ We find that revenue is insufficient to cover capital costs at current market prices.

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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 at a time when renewable portfolio standards are not binding and wind competes freely in the marketplace. In our model, the CAES is used to reduce the risk of committing uncertain quantities of wind energy and to shift dispatch of wind generation to high price periods. Other sources of revenue (capacity markets, ancillary services, price arbitrage) are not included in the analysis. We present a model to calculate profit maximizing day-ahead dispatch schedules based on wind forecasts. Annual profits are determined with dispatch schedules and actual wind generation values.

We find that annual income for the modeled wind–CAES system would not cover annualized capital costs using market prices from the years 2006 to 2009. We also 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 to make a wind–CAES profitable from trading on the day-ahead market 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 31 U.S. states, renewable portfolio standards (RPS) place mandates on the amount of electricity production from renewable resources (DSIRE, 2011). RPS mandates and penalties for non-compliance vary from state to state. At the federal government level, the primary incentive for electricity production from wind is the production tax credit (PTC). For each unit of energy produced from wind, the generator receives a tax credit during the first 10 years of generation. Additionally, many state and local governments offer tax incentives for renewable energy projects such as accelerated depreciation and reduced or waived property taxes (DSIRE, 2011).

Wind power comprised only 2.9% of the electricity generated in the US during 2010 (EIA, 2011a). However, due to the policies mentioned above, the Energy Information Administration (EIA) of the U.S. expects wind generation to double from 2009 to 2035 (EIA, 2011b). As the share of electricity from wind energy grows, 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.

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. 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 provides a wind farm the

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ability to shift a portion of dispatch from low price periods to periods of peak prices. This is an attractive feature since wholesale electricity prices tend to be low at night when U.S. onshore wind production is stronger than during the day.

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 (2011) 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. Since forecast uncertainty is dependent upon location, this analysis is specific to the data we acquired. Furthermore, it should be mentioned that aggregating wind farm forecasts reduces uncertainty (Focken, 2002).

Electrical energy is sold either through bilateral contracts or wholesale markets (day-ahead or real time). Currently, most wind generation in the U.S. is sold through bilateral power purchase agreements (PPA) to utilities that pay an agreed per-unit price for all electricity produced over a 15–25-year period (Harper et al., 2007; Windustry, 2010). PPAs guarantee that all energy will be sold, and remove the risk of price fluctuations inherent in wholesale 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.

Here we analyze the economic viability of selling energy on the day-ahead market from a wind farm with a compressed air energy storage (CAES) plant. Electricity generated by the wind turbines can either be dispatched directly to the grid or stored in the CAES plant for later dispatch. We created a model to determine dispatch quantities that maximized expected hourly profits 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 profit realized from optimal dispatch. Finally, annualized capital cost estimates were subtracted from the summed hourly profits to determine annual profits.

Future electric grids may have very high levels of wind power capacity. Once a significant amount of electricity generation comes from wind power, it is reasonable to expect that at least a small portion of it will be sold on the day-ahead market. While we use current market prices in our model, we feel that this analysis will provide insight into the problem of coupling wind power with CAES. It should be noted that we do not consider additional revenue from capacity markets or ancillary services. Only day-ahead market income is considered without the benefits of a PTC or RECs, or the obligation to purchase wind required by an RPS. We also exclude the possibility of using CAES for energy arbitrage through the purchase and sale of grid electricity. These additional forms of revenue have been treated in previous papers (e.g. Fertig and Apt, 2011) and are not in the scope of this paper. This paper is organized into 4 sections. Section 2 describes the model used to determine the hourly day-ahead dispatch quantities and annual profit. Results from the model are presented in Section 3. Finally, conclusions are presented in Section 4.

2. Model

2.1. Overview

The model we present in subsequent sections uses wind forecast and market price data to determine the profit maximizing dispatch schedule from a wind–CAES system for the day-ahead market. For each hour of the following day, there are two decisions to be made; the amount of energy to dispatch and the amount of energy to store. Since the supply of energy from the wind farm is stochastic, we maximize expected values for hourly profit. The expected profit is a non-linear function of available wind energy and is calculated from a Monte Carlo routine using randomly drawn values of possible wind generation. The wind samples come from empirical probability density functions that were created with historical wind forecast and wind generation data. We found that a sample size of 100 values provided adequate results without requiring too much computational time. We programmed the model with FORTRAN code using dynamic programming to solve the optimization problem by cycling through many different energy storage levels for each hour of the dispatch period. For each storage level, maximum expected hourly profits were determined considering the present hour and all remaining hours in the time horizon.

2.2. 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 GW of pumped hydro storage exist in U.S. grids (EIA, 2010a), but only two CAES facilities exist worldwide, with others under development (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 standalone gas turbines (Succar, 2011).

Round-trip efficiency is an important parameter used in quantifying an energy storage system. For the case of CAES plants, energy input comes from two different types of energy sources. This complicates the round-trip efficiency metric. Succar (2011) showed that using commonly accepted values for CAES plants gives a round-trip efficiency around 82%. However, in this model we are interested in the ratio of energy output to energy input. For every 1 MWh of wind energy stored in a CAES facility, roughly 1.2–1.8 MWh of energy can be supplied due to the addition of natural gas energy (Succar, 2011).

2.3. Wind forecasts

Dispatch decisions in the day-ahead market are made a day before wind generation occurs meaning that participation for wind farms requires good wind forecasts. While dispatch

quantities need to be calculated for a 24 h period, a wind farm with CAES will use longer forecast look-ahead times to optimally manage energy storage levels over a multi-day period. Our model uses 48 h of prediction values to make dispatch decisions for a 24 h period.

Forecasts are received and used for dispatch calculations the day before the dispatch is carried out. Our model assumes that dispatch quantities are submitted at noon on the day prior to dispatching electricity. Forecast values for wind power starting at midnight are used for dispatch calculations, and the first twelve hours are discarded. Fig. 1 illustrates the timeline and wind forecast period for day-ahead dispatch used in the model described later.

We obtained hourly wind forecast and generation data from a single wind farm for this study. The data span a period of 2 years starting at the beginning of 2008 and ending at the end of 2009. Data collection problems resulted in several gaps in the data. Since most gaps spanned a time period of several hours, all gaps were discarded from the dataset. Two hundred eighty-five days of wind data remained in the 2008 period, and 325 days remained in the 2009 period after removing bad data.

In order to characterize forecast uncertainty, we used the 2008 data to create empirical probability density functions of wind generation conditioned on the forecast value. For a given forecast value, the expected hourly profits are calculated using the wind generation probability density functions. The 2009 data were used as inputs for the dispatch model and assumed to have similar uncertainty as the 2008 data.

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). Fig. 2 shows the MAE and RMSE plots for the 2008 wind farm data.

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 11 power classes for each hour of the forecast time horizon. Fig. 3 shows the mean absolute error and RMSE values for each power class 18 h after the forecast was made. Uncertainty bars indicate the shape of the two graphs is very similar.

Within each power class the forecast error probability density function was calculated empirically using 2008 forecast data. This produced a total of $11 \times 48 = 528$ different probability distributions. This method is based on Bludszuweit et al. (2008) who divided forecast values into 50 power classes and fit a beta

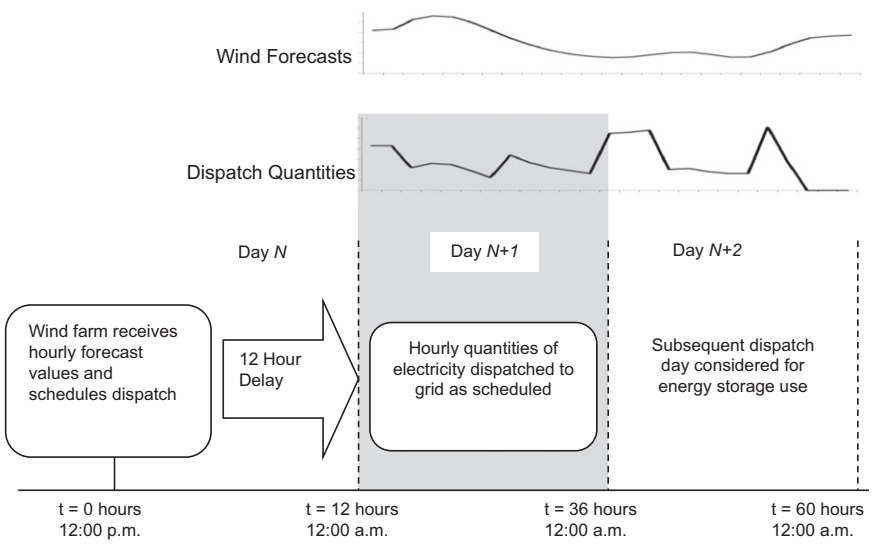

Fig. 1. Wind forecast and dispatch quantity periods used along with timelime for participation in the day-ahead market. The market closes at noon each day. Dispatch quantities are calculated for two days with the first day values submitted to the market.

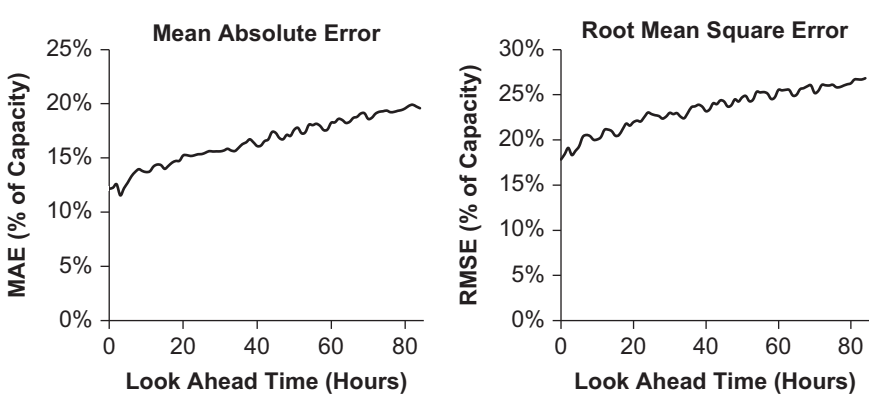

Fig. 2. MAE and RMSE graphs for wind power forecasts with an 84 h look-ahead time. The graphs were made with 2008 data from a single wind farm. Note that all values are normalized by the wind farm capacity.

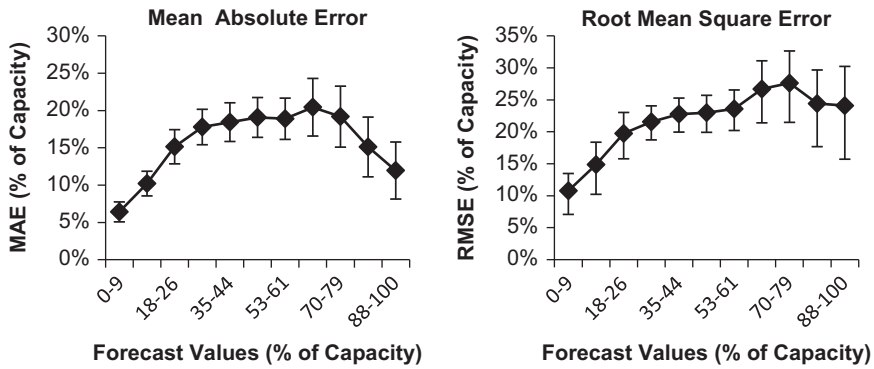

Fig. 3. The mean absolute error and root mean square error as a function of forecast power classes 18 h after the forecast was taken (6 h into the dispatch schedule) for 2008 for the wind farm used in this study.

distribution to the forecast errors within each class. We chose to use empirical probability density functions of forecast errors for each class of forecast values.

As discussed later in Section 2.5, the expected hourly profits from wind–CAES dispatch are calculated with non-linear equations. For this reason we replaced point values in the forecast with empirical pdfs of wind generation. Using Monte Carlo simulations, the wind generation pdf was sampled multiple times to determine the expected hourly profit for each hour of the trading day.

2.4. Wind with CAES

A wind farm operator selling energy on the day-ahead market will determine optimal hourly energy commitments which maximize the wind farm's hourly profit. Hourly profit is defined as hourly income from energy sold to the market less the cost of using energy from CAES. We assume the marginal cost of energy from the CAES changes with the price of natural gas, but the heat rate remains constant. Annual profits are the cumulative hourly profits 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, (3) transmission is not constrained and (4) the wind farm is not participating in non energy markets (e.g. ancillary services).

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 (see previous section). 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 profit 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.

The CAES output power was sized to be 45% of the wind capacity. This size provided the highest annual profit values over eight different price scenarios used in the model (Section 2.7). Ramping capabilities of CAES are much faster than the time resolution of our model (Succar, 2011). Therefore, we neglect the ramp up and down times of the CAES output. Sensitivity analysis on the base case parameters is presented in Section 3.

Table 1
Base case parameters for wind–CAES system used in optimization model.

Wind power capacity factor	0.31
Wind generation per installed MW of capacity	2716 MWh
CAES expander capacity to wind farm capacity ratio	0.45
Expander to compressor power ratio	1
Energy output to energy input ratio	1.35
Storage capacity	15 h
Heat rate	4000 Btu/kWh
Variable cost of storage	$3/MWh

The wind farm hourly optimal dispatch quantities for the day-ahead market were computed with a dynamic programming model coded in FORTRAN. 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 expected hourly profit from day-ahead market electricity sales. Constraints and exogenous variables are explained in the next sections. Dispatch schedules are based on wind power forecasts and market prices. Uncertainty of wind generation was modeled with empirical probability density functions 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 profits gained from the dispatch quantities.

2.5. Optimal dispatch

A wind energy provider will offer energy in the market according to a schedule that maximizes profits. The objective of optimizing hourly profit over T periods is given by

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

Hourly profit is given by π_t and is a function of the hourly energy storage levels, S_t, and hourly energy dispatch quantities, Q_t. The solution of Eq. (1) gives the set of dispatch quantities that will maximize hourly profits over the time horizon T. While we are interested in dispatch quantities for a 24 h period, we solved Eq. (1) for a time period of 48 h and used only the first 24 h. Using a time horizon of 48 h allows optimal management of the energy storage for the dispatch day while considering trading for the next day.

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, 2004). Rather than having uncertain demand, as is

common in operations research, the supply of wind energy for storage or dispatch is treated as uncontrollable and stochastic. Dynamic programming is well suited to multistage processes such as energy dispatch from storage. Eq. (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 time intervals from t to T.

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. Uncertainty of energy supply was modeled with empirical wind generation probability density functions. For more information on dynamic programming models with stochastic supply see Nandalal and Bogardi (2007).

An illustration of the optimal dispatch algorithm is shown in Fig. 4 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 profit over the time horizon. 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.

Three things should be noted in Fig. 4. First, this algorithm limits energy storage levels to 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 constrained by the CAES power. If the CAES is fully charged, it cannot use all stored energy in one hour because the expander can only produce electricity at a rate up to its rated power. This is illustrated in Fig. 5. 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, profits for all possible transitions in the energy storage level were calculated. For each storage level transition the dispatch quantity giving the largest expected profit for the current and all remaining hours was determined. Once all transitions have been analyzed, the optimal path for the amount of energy stored in the CAES is determined to give the maximum profit. Expanding the marginal profit function in Eq. (1) produces Eq. (2). Marginal profit for each hour denoted by the subscript t is calculated as income from electricity sold less the cost of using energy from the CAES.

$$\pi_t = \begin{cases} Q_t p_t - c_S s_t^e & \text{if } Q_t \le W_t^e + s_t^e \\ (W_t^e + s_t^e) p_t - (Q_t - (W_t^e + s_t^e)) p_t \alpha - c_S s_t^e & \text{otherwise} \end{cases} \quad (2)$$

where

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

Total energy available for dispatch during any given hour is the sum of the estimated wind generation (W^e) and the expected amount of energy used from CAES (s^e) during that hour. The superscripts indicate that the variable is estimated. When energy is added to the CAES the value for s^e is zero. Otherwise s^e is equal to the decrease in stored energy (ΔS) multiplied by the energy output to input ratio (η).

When dispatch does not exceed total available energy, profit is the dispatched quantity (Q) multiplied by the market price (p) minus the cost of using energy from storage ($c_s s^e$) as shown in the first line of Eq. (2). The parameter c_S represents the marginal cost of using energy from CAES. If energy is overcommitted, profit is calculated from the second line in Eq. (2) as total available energy ($W^e + s^e$) multiplied by the market price less the cost of purchasing additional energy in the market to meet the obligation.

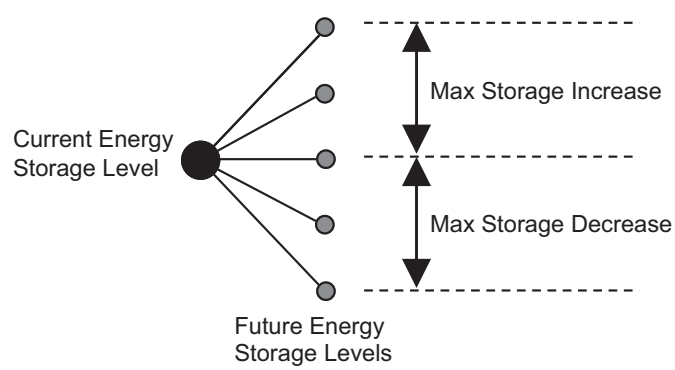

Fig. 5. Illustration of five possible energy storage level transitions during one hour for a given current energy level. The limitation to transitions of ± 2 levels represents the CAES charge/discharge rate limitation. In the actual model, transitions covered many more than 2 levels.

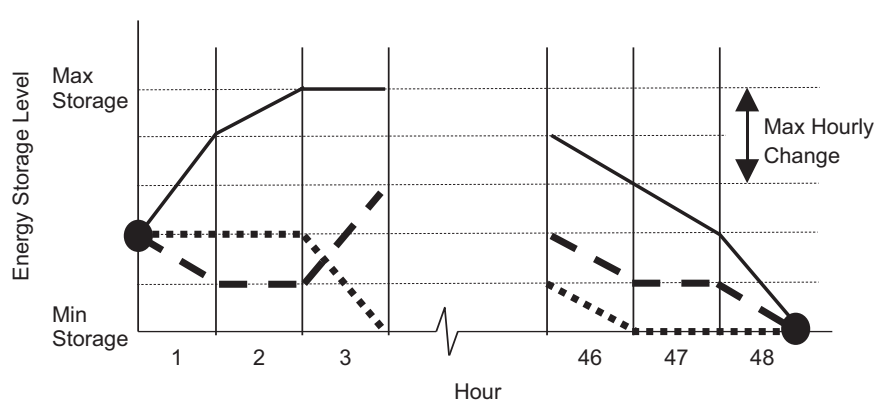

Fig. 4. Illustration of potential energy storage level changes during the optimization horizon.

A weighting factor (α) is also used in the second line of Eq. (2) to reduce the occurrence of overcommitments. Offering too much energy on the market can be costly and lead to negative profit. Therefore, we increased the effect of overcommitments on the objective function by using a large weighting factor which improved actual profits.

Calculating hourly profits occurs before the wind generation values are known so we must maximize expected profits each hour. Since wind generation is a random variable, we used Monte Carlo sampling to draw a sample of wind generation values from empirical probability density functions. For every storage transition inspected in the model, the expected hourly profit was computed according to Eq. (2) for all wind generation values drawn in the sample. A sample size of 100 wind generation values provided adequate results. As stated earlier, we created empirical probability density functions using the 2008 wind data. Given the wind forecast value and look-ahead hour, the appropriate pdf was used for the Monte Carlo sampling.

The optimization formulation used in this model is expressed fully as the maximization of expected profits for a 48 h period as shown below where E [] denotes the expected value.

$$\max_{\{Q_t,S_t\}} \sum_{t=1}^{T=48} E[\pi_t] \tag{3}$$

$$\text{s.t.} -P^E \le \Delta S_t \le P^C \tag{4}$$

$$\Delta S_t \le E[W_t] \tag{5}$$

$$0 \le S_t \le C \tag{6}$$

$$0 \le Q_t \le \left(P^E + W^U\right) \tag{7}$$

Eq. (3) expresses the objective function as the expected profit over a 48 h period. Accumulation of stored energy during a one-hour interval cannot exceed P^C, the rated power of the CAES compressor. Alternatively, the maximum drop in stored energy is the negative value of the rated power of the expander in the CAES, P^E. These constraints are expressed in Eq. (4). Eq. (5) states that the storage level cannot increase in an hour by more than the expected wind generation for that hour. Eq. (6) states that the energy storage level cannot exceed the storage capacity, C. Eq. (7) constrains hourly dispatch to a positive value not greater than the sum of the wind farm capacity and the output power of the CAES, P^E.

2.6. Realized profit

Hourly dispatch quantities resulting from the optimal dispatch algorithm are used with actual wind generation values to determine hourly profits. In this part of the model, Eq. (8) is used to calculate realized hourly profits. When scheduled dispatch (Q) is less than available energy, hourly profits are calculated with the first line. This is calculated as the revenue from the sale of dispatched energy plus the sale of excess, non-scheduled energy (q) minus the cost of energy pulled from the CAES. Excess energy occurs when the CAES system is filled to capacity or the amount of excess wind generation is beyond the CAES compressor charge rate. Revenue from excess energy is reduced by the factor $(1-\varphi)$, where φ is the market penalty factor and has a value between 0 and 1.

The second line in Eq. (8) is used when dispatch is greater than available energy. Here profit is calculated as revenue from all available energy minus the cost of purchasing overcommitted energy minus the cost of using stored energy. The market penalty factor is used here to increase the cost of purchasing energy by the amount $(1+\varphi)$. In our model we used the value 0.2 for φ which increases the cost of overcommitted energy by 20% and decreases revenue from excess energy by 20%.

$$\pi_t = \begin{cases} Q_t p_t + q_t p_t(1-\varphi) - c_S s_t & \text{if } Q_t \le W_t + s_t \\ (W_t+s_t)p_t - (Q_t-(W_t+s_t))p_t(1+\varphi) - c_S s_t & \text{otherwise} \end{cases} \tag{8}$$

where

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

Eq. (8) is applied to each hour of the year. After each hour, the amount of stored energy is updated. During hours when dispatch is less than the wind generation, stored energy accumulates up to the storage capacity within the CAES charge limit. When dispatch is greater than wind generation, the storage level is reduced to make up the difference. Each hour that dispatch quantities cannot be met with available wind generation and energy storage (within CAES limitations) energy must be purchased to make up the difference.

In summary, the model maximizes expected hourly profit for a wind–CAES system operating in the day-ahead market. The decision variables are the expected hourly dispatch and storage quantities. Expected hourly profit is calculated via Monte Carlo sampling of wind energy generation from empirical probability density functions. Optimal dispatch quantities are then used to determine profit for one year. Since our data limited us to 325 days, we scaled up the summed hourly profits to estimate 365 days.

2.7. Market clearing price data

We ran the model with eight different market price scenarios to observe how the results change with market prices. Four separate years, 2006–2009, of wholesale market prices from the western zone of the Electricity Reliability Council of Texas (ERCOT) and the Iowa zone of the Midwest ISO (MISO) market were used for the eight price scenarios. Prices for ERCOT came from the balancing market while MISO prices were from the day-ahead market. ERCOT had no central day-ahead market during the years covered with the data. Over 90% of energy traded in ERCOT is through bilateral contracts. However, the average bilateral contract price in 2009 was similar to the average balancing market price, although balancing prices were more volatile (Potomac Economics, 2009). We used market prices from these regions because they have high levels of wind capacity compared to the rest of the US. Note that each year of price data was treated as a separate price scenario and run with the same year of wind data. Descriptive statistics for each price scenario are shown in Table 2.

MISO prices have been less volatile than ERCOT prices, primarily because balancing market prices were used for the ERCOT scenarios. 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, 2011).

3. Results

3.1. Wind and CAES annual costs

Lawrence Berkley Laboratory found that a sample of 181 wind farms built in 2009 and 2010 had an average capacity-weighted cost of \$2.1 million per MW with a range from \$1.3 to over \$4 million per MW (Wiser and Bolinger, 2011). The Energy Information Administration estimates the average wind installation cost at nearly \$2 million per MW (EIA, 2010b). A range of wind farm

Table 2
Market price statistics for the eight price scenarios used in the model. All values are in U.S. dollars per megawatt-hour.

Scenario	Market	Year	Mean	Std. dev.	Min	Max
1	ERCOT (West zone)	2006	51.37	31.91	−209.49	823.75
2		2007	52.86	51.67	−407.91	929.99
3		2008	54.64	84.37	−523.20	2076.30
4		2009	25.89	41.53	−235.38	1664.30
5	MISO (Iowa Zone)	2006	42.72	26.30	2.86	329.51
6		2007	49.89	28.52	3.23	236.59
7		2008	47.75	37.94	−233.52	449.72
8		2009	24.09	21.08	−133.27	284.00

Table 3
Wind and CAES base case cost estimates.

	Wind farm	CAES plant
Capital cost ($/MW)	2 million	0.75 million
Fixed annual cost ($/MW)	30,000	10,0000
Economic life (years)	25	25
Discount rate (%)	10	10
Total annual cost ($/MW)	192 thousand	71 thousand

costs arise due to differences in site requirements and fees. Based on cost numbers in the literature above, we assume a range of installation costs from $1.5 to $2.5 million per MW.

CAES cost estimates also span a large range 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 $0.6 to $0.9 million per MW of expander capacity for storage sizes in the 15–20 h range (Denholm and Sioshansi, 2008; Sullivan et al., 2008; EPRI-DOE, 2004). Table 3 shows base case cost estimates used in this study for a wind farm and a CAES facility.

Annual nominal costs for a wind farm and CAES facility were calculated for the full range of cost values assuming a discount rate of 10% representing the blended cost of capital. In our uncertainty calculations we used a range of discount values from 6% to 14%. Based on our range of estimates discussed above, annual costs for a wind farm range from $145 to $240 thousand per MW of installed capacity. Annual costs for the CAES facility range from $55 to $85 thousand per MW of expander capacity.

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 $70 per MWh through a PPA, the wind farm will receive $184 thousand per MW of capacity annually. Wiser and Bolinger (2011) calculated the average price of wind power from farms constructed in 2010 to be $73 per MWh (sample size = 26 projects). This does not include the PTC of $22 per MWh or revenue from the sales of renewable energy credits. Once the PTC is included, the revenue increases to $240 thousand per MW of installed capacity.

3.2. Annual profits

Results from the model presented in Section 2 are shown in Fig. 6. For all price series used in the model, the annual profits were negative. The model was run multiple times to determine the CAES power output value that produced the highest average annual profit for all price scenarios. Price scenarios 4 and 8 came from 2009 data when electricity prices were quite low resulting in much less profit for the simulated wind farm. Scenarios 1 through 4 came from ERCOT which had higher prices and higher volatility

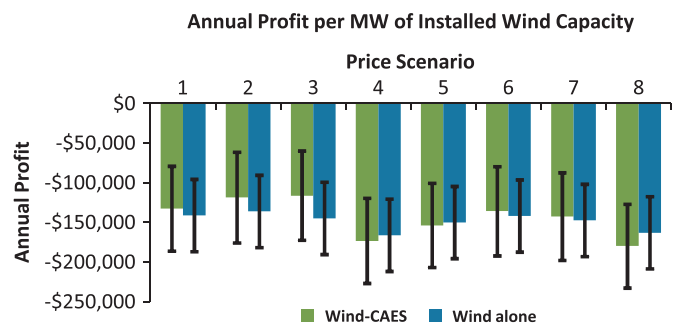

Fig. 6. Annual profits for the wind farm with CAES using eight different market price input scenarios. All profits are negative (i.e. losses). Uncertainty ranges were created by running the model with different cost assumptions for the wind–CAES system.

than MISO leading to higher profits. The CAES system was able to take advantage of the greater spikes in the ERCOT prices.

Annual profits for the wind–CAES system are shown alongside annual profits for a standalone wind farm. Scenarios 4, 5 and 8 have low prices and low volatility resulting is more loss when CAES is added. For these scenarios, the CAES value is less than its costs.

The model assumes that overcommitted energy must be purchased from the wholesale market to meet the wind farm's contractual obligation. In using a market penalty factor equal to 0.2, we assumed that overcommitted energy is purchased at 20% above the day-ahead price and excess energy is sold at 20% below this price. In Section 3.4 we show how profits for scenario 6 change with a range of penalty factors.

If the wind farm with CAES is paid a direct subsidy equal to its annual loss, we can determine the cost of carbon emissions avoided in this situation. These costs would be reduced if revenues for ancillary services or price arbitrage were included. The amount of carbon emissions displaced by the wind–CAES system 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 4 expressed in dollars per tonne of carbon dioxide emissions avoided.

Due to CAES limitations, a small fraction of the wind energy generated beyond scheduled dispatch cannot be stored. Fig. 7 shows the excess, non-stored energy for each price scenario for the wind–CAES and standalone wind farm. Fig. 8 shows the amount of overcommitted energy for each price scenario. Adding a CAES plant to the wind farm reduced overcommitted energy by roughly half.

3.3. Annual profit with perfect forecasts

Since the overcommitted energy results in profit loss for the wind farm, wind forecast accuracy directly affects the profits of

Table 4
Cost ranges for each tonne of carbon dioxide emissions avoided with the wind farm and CAES.

Price scenario	Cost range per tonne of carbon dioxide
1	$60–150
2	$45–130
3	$45–130
4	$130–240
5	$80–180
6	$60–150
7	$70–160
8	$125–220

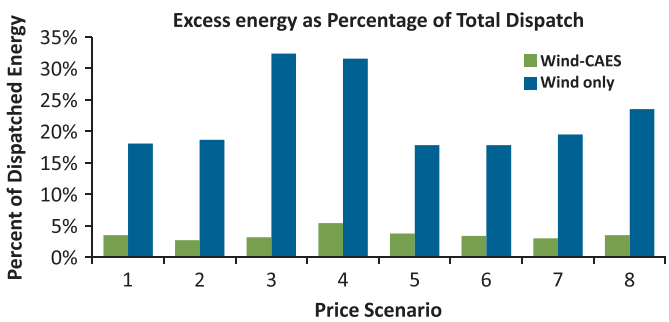

Fig. 7. Excess, non-stored energy as a percentage of total dispatch for each price scenario used in the model (base case cost assumptions).

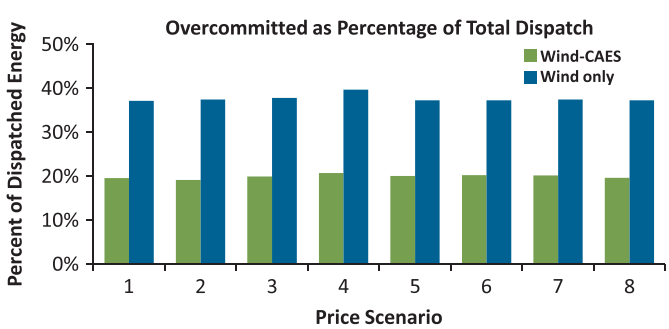

Fig. 8. Overcommitted energy as a percentage of total dispatch for each of the price scenarios used in the model (base case marginal costs for stored energy).

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. Results are shown in Fig. 9, which indicate an upper bound to the profits that can be obtained with improved forecasting techniques. As indicated in the figure, perfect wind knowledge reduces annual losses and also brings profits from the standalone wind farm more in line with the wind–CAES system. All price scenarios still produce annual losses.

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 price scenario 3 (ERCOT 2008) provided the largest annual profit, we used these prices with base case cost assumptions for stored energy to determine how the profit might change if storage parameters are altered. This was done for storage capacity, ratio of CAES expander to compressor power rating and CAES energy output to energy input ratio. For the base case assumptions with scenario 3, annual profit was calculated to

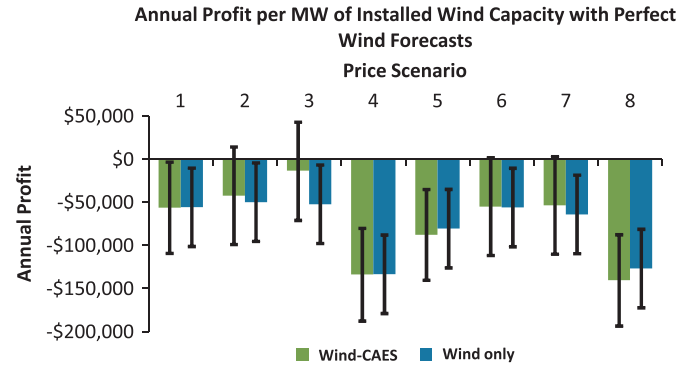

Fig. 9. Annual profit per installed MW of capacity with perfect wind forecasts for each price scenario. Uncertainty bars were created by running the model with different cost assumptions for the wind–CAES system.

be—$116,000 per MW of installed wind capacity. Sensitivity results are shown in Fig. 10.

Annual profits would improve modestly with better efficiency, more charging power and more storage. This assumes that these improvements could be made without increasing the cost of the CAES. It is apparent that the model is still far from giving positive results for the profits.

We assumed a 20% penalty costs occurred when additional energy had to be purchased in order to fulfill a day-ahead contract. We show the sensitivity of our results to the penalty factor in Fig. 11 using price scenario 6. Profits decrease linearly as the penalty factor is increased. The wind farm without CAES suffers more from higher penalties due to the large amounts of overcommitments.

3.5. Annual profit with a CO2 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 are interested in knowing how carbon prices affect the profitability of the wind–CAES system in our model. Since the wind–CAES system in our model is constrained to storing energy only from the wind farm, and we are only considering profits from the day-ahead market, these results do not apply to wind farms in general. 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 described 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 load data to estimate market prices. 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, after separating prices by season, we were able to get estimated average hourly prices within 15% of 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 a 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 merit order in the marginal cost curve will change only slightly for carbon prices up to $50 per tonne. To get price inputs for the model in the hypothetical carbon dioxide pricing situation we first subtracted our estimated prices without

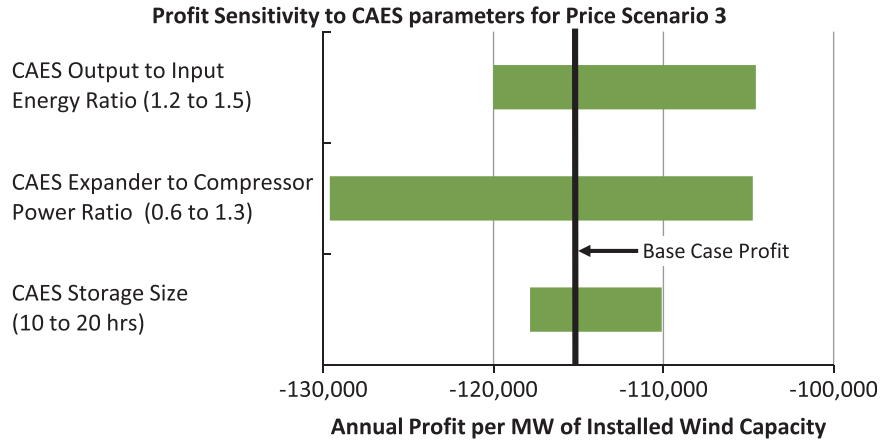

Fig. 10. Sensitivity of three selected CAES parameters on annual profit results from the model used in this study.

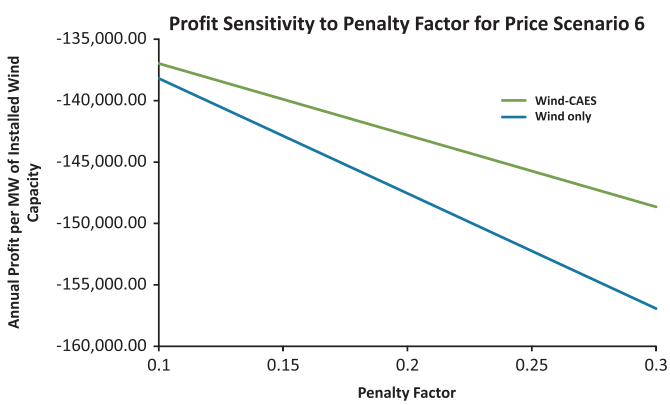

Fig. 11. Sensitivity of annual profit to the market penalty factor for price scenario 6.

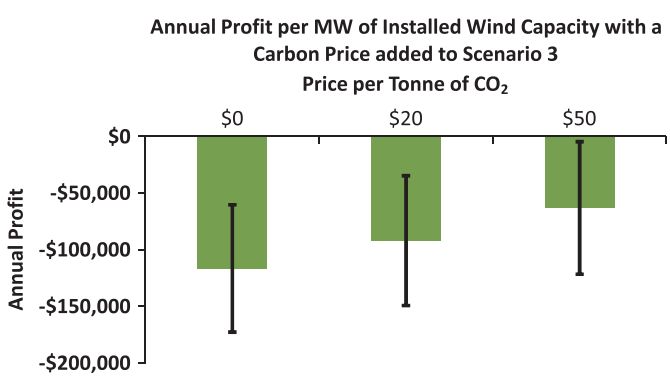

Fig. 12. Annual profit per installed MW of capacity with carbon prices included in price scenario 3 (ERCOT 2008). Uncertainty bars were created by running the model with different cost assumptions for the wind–CAES system.

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.

Fig. 12 shows our results for carbon prices of $20/tonne and $50/tonne. The EU carbon trading price for 2011 fluctuated between $13 and $26/tonne (Turner, 2011). A $20/tonne price on carbon dioxide may be possible with the higher price much less likely in the U.S. As evidence, the American Clean Energy and Security Act of 2009 was expected to create a price of $15/tonne rising to $26 by 2019 (CBO, 2009), however it failed to become a

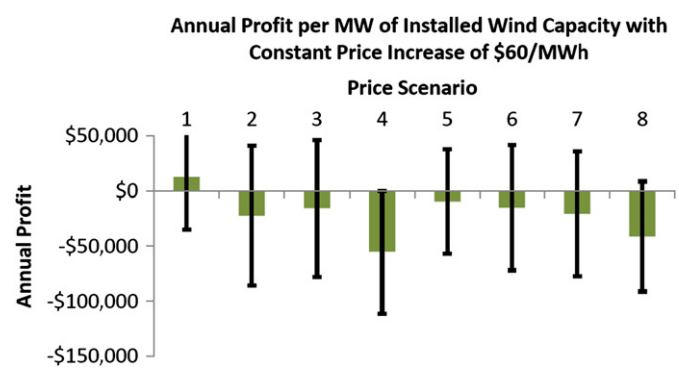

Fig. 13. Annual profits per installed MW of wind capacity with a constant price increase of $60 per MWh using eight different market price scenarios. Uncertainty bars were created by running the model with different cost assumptions for the wind–CAES system.

law. Anything beyond a $50 per tonne price on carbon dioxide seems impossible in the near future in the U.S.

A carbon dioxide price of $50 per tonne resulted in annual losses for the wind–CAES system. Price scenario 3 was much more favorable for the model than the other scenarios tested. Revenue from the day-ahead market with a carbon dioxide price would not cover the capital costs. 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 wholesale electricity 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 our hypothetical wind–CAES system 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. Fig. 13 shows the annual profit for each price scenario along with the estimated annual costs explained earlier. The uncertainty bars span above zero in seven of the price scenarios indicating that a wind–CAES system with low capital costs would be profitable with this subsidy.

4. Conclusions and discussion

In time, wind generation may grow to the point where it no longer needs tax support and RPS obligations, and must bid into

markets as do other generators. We investigated the option of reducing dispatch uncertainty in systems with very large wind energy by trading wind power in day-ahead markets from a wind–CAES system. In this case, the CAES was sized and used for the sole purpose of reducing the risk associated with dispatch uncertainty. Other potential revenue streams such as grid electricity arbitrage, ancillary services, and capacity markets were not considered.

The profitability of collocating a CAES plant with a wind farm to allow participation in the day-ahead energy markets is dependent on several factors including (1) the uncertainty of wind power forecasts, (2) wholesale market prices and (3) wind generation capacity factor. We analyzed one wind–CAES example with eight different market price scenarios using data from ERCOT and MISO to determine its economic viability. In the case studied, it was shown that adding a CAES plant to a wind farm did not provide the ability to make a profit trading energy in the day-ahead market. A wind farm in a more favorable location may have different results since forecast accuracy, markets prices and wind resources vary from one location to another.

Costs and forecast uncertainty are the largest contributors to the unprofitability of the modeled plant. Forecast uncertainty can be reduced significantly by aggregating wind farms (Focken et al., 2002). A CAES plant centrally located among multiple wind farms may allow wind trading on the day-ahead market. In this scenario, the CAES dispatch would be optimized according to price forecasts and aggregated wind forecast accuracy from the corresponding wind farms. One could envision a set of power purchase agreements between the wind farms and the CAES plant.

We find that a wind–CAES system is unlikely to be profitable in the day ahead market without tax incentives or the requirements of an RPS. We examined the effects of a price on carbon (highly uncertain in the USA), finding that a price of $50/tonne CO_2 would not be sufficient for profitability. A large increase in wholesale market prices or a substantial decrease in wind–CAES costs is needed to allow a wind–CAES system used in the manner modeled here to profit from day-ahead energy sales.

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