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The economics of large-scale wind power in a carbon constrained world

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Abstract

The environmental impacts of fossil-fueled electricity drive interest in a cleaner electricity supply. Electricity from wind provides an alternative to conventional generation that could, in principle, be used to achieve deep reductions (>50%) in carbon dioxide emissions and fossil fuel use. Estimates of the average cost of generation—now roughly 4¢/kWh—do not address costs arising from the spatial distribution and intermittency of wind. The greenfield analysis presented in this paper provides an economic characterization of a wind system in which long-distance electricity transmission, storage, and gas turbines are used to supplement variable wind power output to meet a time-varying load. We find that, with somewhat optimistic assumptions about the cost of wind turbines, the use of wind to serve 50% of demand adds ~ 1–2¢/kWh to the cost of electricity, a cost comparable to that of other large-scale low carbon technologies. Even when wind serves an infinitesimal fraction of demand, its intermittency imposes costs beyond the average cost of delivered wind power. Due to residual CO_2 emissions, compressed air storage is surprisingly uncompetitive, and there is a tradeoff between the use of wind site diversity and storage as means of managing intermittency.

Keywords: Wind; Optimization; Carbon

1. Introduction

In 2002, the wind power industry generated total sales of $5.8 billion, with over 32 GW of wind capacity installed worldwide (BTM Consult, 2003). At good sites, the average cost of wind is currently 4–6¢/kWh without credits or subsidies, and advances in turbine design may plausibly reduce the cost to 2¢/kWh in the next two decades. Although wind energy currently represents about 0.1% of total global electricity (Sims et al., 2003), it has the fastest relative growth rate of any electric generating technology: capacity has increased by roughly 32% annually for the 5 years ending in 2002 (AWEA, 2003). The absolute annual growth of wind power generation now exceeds that of hydro, but is still an order of magnitude smaller than for natural gas fired electricity. Several analyses suggest that wind could feasibly serve at least 10–20% of electricity demand globally (EWEA, 2003) or regionally (Ilex and Strbac, 2002; Gardner et al., 2003) within a few decades. The rapid growth of wind capacity and the aggressive projections of future growth are driven by two factors: the declining cost of wind technology and strong policy incentives for wind development.

Two factors—the spatial distribution and intermittency of wind resources—raise the cost of large-scale wind above the average cost of electricity from a single turbine. Additional costs arise from long distance electricity transmission (to compensate for mismatch between the spatial distribution of wind resources and demand) and backup capacity and/or storage systems (to compensate for the mismatch in temporal distribution of supply and demand). While these costs arise at any scale, their influence on the economics of wind-power grow rapidly as wind serves a larger fraction of demand.

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We investigate the economics of using wind to reduce CO_2 emissions in future electric power systems. Our focus is on the utilization of wind to serve more than a third of electricity demand by 2030 in a regulatory environment shaped by carbon constraints. Given the uncertainty about the regulatory and technological paths that the electricity industry might take over the next quarter century, we do not make predictions about the likely mix of generating technologies in 30 years, nor the temporal evolution of the generating mix. We aim to understand the cost-effectiveness of using wind to mitigate carbon emissions in a carbon constrained world, while accounting for the remote location and intermittency of wind resources. We employ a greenfield optimization model that rests on a time resolved simulation of wind power, demand, and storage in order to determine the optimal wind, gas turbine, storage, and transmission capacities in a hypothetical system under a carbon tax.

The timing of serious regulatory constraints on CO_2 emissions remains profoundly uncertain. When such constraints arrive, the electric sector will likely need to deliver deeper proportional reductions in emissions than elsewhere in the economy. There are several reasons to expect that the electricity sector will be a key target for carbon mitigation. Centralized ownership and management of electric power plants, which are the largest and most manageable point sources of CO_2 emissions, make regulation easier to implement in an industry that already has considerable experience with the regulation of emissions (Johnson and Keith, 2004). If serious efforts are made to slow climate change, then the US electric sector will likely need to cut CO_2 emissions in half within the next quarter century. Wind power may play a pivotal role in reducing CO_2 emissions from electric power generation.

There is no panacea for eliminating CO_2 emissions in the electricity sector. Because wind is a viable CO_2 emissions-free technology, a more accurate assessment of the cost of mitigating electric sector CO_2 emissions using wind is important to the economics of climate change mitigation. Other options include fuel switching to less carbon-intensive fuels, improved efficiency (both demand- and supply-side), carbon capture and sequestration (CCS), biomass, nuclear, and photovoltaics. Each of these alternatives possesses a unique set of benefits, limitations, and costs. Although our analysis focuses on wind, we recognize the potential efficacy of these other options.

The rapid worldwide growth in wind capacity has been driven by environmentally motivated taxes, credits, and other regulatory incentives. Absent such incentives, we do not expect that wind will achieve substantial penetration into worldwide electricity markets, despite the continued declining costs of wind turbines, in part because of the costs imposed by remoteness and intermittency at high penetration levels. We assume that the most important driver for future wind development will be a constraint on carbon emissions. Under a strong carbon constraint, it is likely that wind will compete effectively with other means of reducing electric sector carbon emissions such as coal with CCS or nuclear. Despite assertions to the contrary (NREL, 2002; UCS, 2003), wind is unlikely to become a competitive means to achieve reductions in air pollution or to enhance energy security. If air pollution reduction is the goal, then deep reductions in air pollutants can be achieved by retrofits to existing coal facilities at costs of order 1¢/kWh (Rubin et al., 1997). If energy security is the driving concern, then for many nations, coal provides sufficient security. The reserve/production ratio for coal is about 200 years globally, and 250 years in the US (BP, 2003).

Understanding the long-term role of wind in a CO_2 constrained world requires us to bridge two domains of analysis. First, there is a rich set of analyses that examine the integration of wind power into existing electricity transmission systems and their associated electric markets. Such analyses generally look no more than two decades ahead and/or assume that much of the existing electric power infrastructure remains in place (e.g., Grubb, 1988; Hirst, 2001; Ilex and Strbac, 2002). Second, there is a similarly rich set of analyses that examine the long-term economics of the CO_2-climate problem. These include energy models of the kind that participate in the Energy Modeling Forum, and Integrated Assessment models that embed energy system models with models of the climate system and the impacts of climate change to assess climate policy. These models often examine a century long time horizon, and include representations of technological change and economic growth. While these models often include wind, they cannot readily capture the dynamics of load and dispatch in electric power systems and markets (e.g., Edmonds et al., forthcoming). The aim of our analysis is to bridge the gap between these intellectual domains by simulating large-scale wind in a greenfield electric power system. In addition, our analysis provides cost estimates (in the form of supply curves) of mitigating carbon emissions with wind at high penetration levels that could be used in developing more accurate treatments of wind in long-duration comprehensive models aimed at understanding the cost of mitigating CO_2 emissions.

Analysis by Cavallo (1995) addresses the issue by estimating the cost of "baseload" wind (a wind-storage system with 90% capacity factor) at 6¢/kWh. Because Cavallo's analysis focuses on a specific case study of a Kansas windfarm connected to southern California via a 2000 km HVDC line, it is difficult to extrapolate the results to scenarios that include multiple wind sites, where the utilization of weakly correlated wind sites might improve the economics.

Recent analysis by Ilex Energy Consulting (2002), examined the balance of system costs incurred by renewables serving 20% and 30% of electricity demand in Great Britain. In the North Wind scenario with high demand, the additional system cost due to wind energy serving 30% of electricity demand is ~ 1.8 ¢/kWh (Ilex and Strbac, 2002). However, the analysis does not include the cost of the wind turbines or the cost of new transmission to tie the wind farms to the grid—only the system costs incurred for grid reinforcement, managing transmission losses, balancing, and security.

The National Renewable Energy Laboratory is developing a model called the Wind Deployment Systems Model (WinDS), a multi-regional, multi-time-period, GIS and linear programming model. Preliminary results indicate that in the base case (with infinite extension of existing regulatory incentives) wind capacity may reach several hundred GW in the next 50 years (Short et al., 2003).

In contrast to the studies mentioned above, we focus on the cost-effectiveness of large-scale wind in meeting a CO_2 constraint. In order to do this, we simulate the interaction of several large wind farms and a time-varying demand in a greenfield scenario, where wind, storage, transmission lines, and gas turbines are optimized to meet load on an hourly basis. Our analysis builds on Cavallo's work by including multiple wind sites in order to quantify the benefit of geographically dispersed wind farms, which exhibit greater aggregate reliability by exploiting less correlated wind patterns. At the same time, our analysis is meant to be transparent and generalizable, in contrast to the Ilex analysis (2002) and NREL's WinDS model which are detailed policy analyses with a strong national focus.

The following section describes the challenges posed by the spatial distribution and intermittency of wind resources. Section 3 describes the structure, assumptions, and results of our model. Section 4 provides a more detailed analysis of the role of storage in large-scale wind systems under a carbon constraint. Finally, Section 5 provides a summary of the model results and draws conclusions for the future of large-scale wind energy in the long-term.

2. Intermittency and location

The intermittency of wind energy can affect an electricity grid on timescales ranging from less than a second to days. Three timescales concern system operators on a day-to-day basis: minute-to-minute, intrahour, and hour- to day-ahead scheduling. System operators employ an automatic generation control (AGC) system to manage minute-to-minute load imbalances—an ancillary service known as regulation. Operating reserve, which consists of spinning and non-spinning reserves, represents capacity that can be dispatched within minutes to respond to forced outages or fluctuations in intrahour load. The requirements for operating reserves are generally set by deterministic criteria, such as a fraction of the forecasted maximum peak demand or large enough to compensate the most likely or largest contingencies. To meet forecasted demand using economic dispatch, system operators schedule units to produce a specified amount of energy hours or days in advance.

Intermittency can affect system operation on all three timescales, but the impact depends on the transmission and generation infrastructure, and the resulting costs are not well understood in cases where wind serves more than a small fraction of demand. While Denmark and parts of Germany have wind serving more than 20% of demand, their experience does little to resolve uncertainties about the costs imposed by intermittent wind resources for at least two reasons. First, both are connected to large power pools that serve as capacity reserve for wind. Second, the multiplicity of wind energy subsidies and absence of efficient markets, particularly markets for ancillary services, makes it difficult to disentangle costs. All else equal, the cost of intermittency will be less if the generation mix is dominated by gas turbines (low capital costs and fast ramp rates) or hydro (fast ramp rates) than if the mix is dominated by nuclear or coal (high capital costs and slow ramp rates).

Current wind farm capacities are small relative to the overall generation capability within the control area they serve, so system operators can treat wind power as negative load and compensate unpredictable wind output by using standard load-following control procedures (Richardson and McNerney, 1993). The effect of wind on a minute-to-minute and intra-hour timescale is an important issue, and has been investigated by Hirst (2001) and Fairley (2003). In a hypothetical scenario where a 100 MW wind farm near Lake Benton in southwestern Minnesota is connected to the PJM grid, Hirst (2001) finds that the cost of intrahour imbalance charges is 0.07–0.28 ¢/kWh and the cost of regulation (AGC) due to the variable wind power is 0.005–0.030 ¢/kWh. Fairley (2003) reports on plans to install 30–40 MW of wind on the 150 MW Hawaiian grid, with a combination of power electronics and advanced energy storage (e.g. flow batteries) installed to correct supply and demand imbalances. Wind intermittency also complicates economic dispatch, particularly when wind serves a large fraction of demand, because the system operator must balance the risk of wind not meeting its scheduled output against the risk of committing too much slow-start capacity (Milligan, 2000). It is important to note that wind is fairly predictable over a daily timescale, and that accurate wind speed forecasts provide an important tool to system operators scheduling energy. As wind farms increase in size relative to the control area, the amplitude of power fluctuations from intermittent wind energy increases, making it difficult for system operators to utilize limited reserve to compensate for periods of low wind power output (Richardson and McNerney, 1993). However, even at the margin, adding wind power will decrease reserve margins.

If wind were to serve a third of demand, cost-effective management of intermittency would become a central issue for electric infrastructure and associated markets. Intermittency can be mitigated by constructing storage facilities or backup capacity integrated with large wind farms and/or by adding load following capacity to the wider grid. Storage and backup reduce the imbalance penalties paid by wind generators to the system operator, but add to the cost of the wind project whereas managing intermittency elsewhere in the grid will decrease the average price paid to the wind farm operator. Intermittency will raise overall costs under either scenario. In the model described below, we ignore market mechanisms, and search for solutions that minimize the overall costs and intermittency.

While not addressed here, increasing the price-responsiveness of demand on a short timescale is a potentially important alternative method for managing wind's intermittency. Several options exist for making demand more responsive to price. First, residential customers can be provided with real-time monitors that track energy consumption and price; but demand response is weak, particularly at the short timescales of economic dispatch. A recent experiment with electricity monitoring devices in Japanese households, for example, found that monitor usage had very modest impacts on energy conservation: each day a household accessed the monitor, daily electricity usage decreased by −1.5% on average (Matsukawa, 2004). A second, and likely more effective option, is to encourage residential customers to allow system operators to control appliance loads. Modeling work that employs refrigerators in the UK as responsive loads demonstrates that the aggregation of load-responsive appliances can offer some of the benefits of spinning reserve, provide operational flexibility by delaying the fall in frequency at times of imbalance, and provide considerable frequency smoothing when operated in conjunction with wind power (Short, 2003). Third, and likely most important, are the options that arise for commercial and industrial loads in liberalized electricity markets. For example, customers can submit price-responsive demand curves in day-ahead markets for energy and ancillary services that provide the system operator with increased flexibility in matching supply with demand (Hirst, 2002).

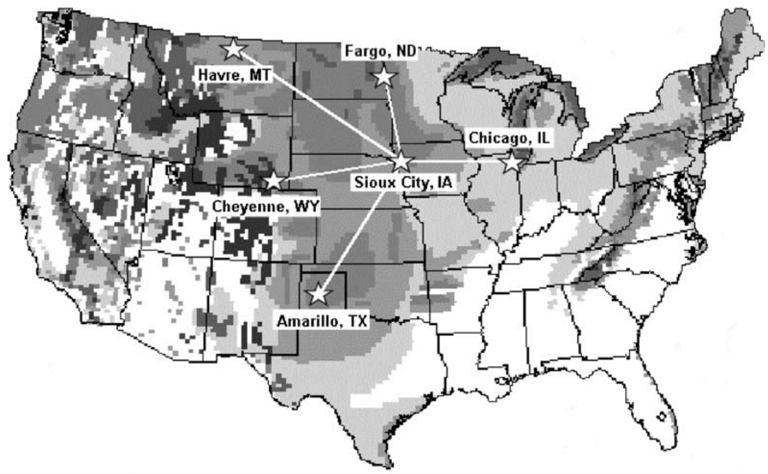
All else equal, responsive demand will reduce the need for reserves, lowering overall electricity supply costs; and, all else equal, wind power will increase the need for reserves. The interactions between these effects have not been explored: it is possible, for example, that the marginal cost of wind's intermittency will be roughly independent of demand responsiveness.

The second challenge posed by wind is the spatial distribution, and often remote location, of high-quality, large-scale wind resources. Current windfarm installations in both the US and abroad have generally been sited in strong wind resources close to preexisting transmission infrastructure. Wind sites near demand are not likely exploitable on a large scale for two reasons. First, these resources tend to be of lower quality (Fig. 1) such that when wind is used at sufficient scale to exploit economies of scale in long distance transmission lines, it will be more economical to import electricity from distant high quality wind sites. Second, the high quality wind sites that do exist near demand centers are generally in environmentally sensitive areas and/or areas where there will be significant public opposition. In the US, the controversy surrounding the Cape Wind project is testimony to the uproar created by proposals aimed at building wind farms in an area that is both a popular recreational center and environmentally sensitive (Grant, 2002; Ziner, 2002). Undeveloped areas near demand centers suitable for wind development, such as mountain ridges and coastal areas, tend to be naturally popular recreational areas of significant importance to local residents.

If wind were used to serve a significant fraction (e.g., one-third) of US electricity demand, then the need for cheap land, low population densities, and strong wind resources will likely dictate that the bulk of the wind capacity be located in the remote, windy regions of the Great Plains and transmitted via long-distance transmission lines to demand centers. There is no shortage of capacity: under moderate land use constraints on wind farm siting, 12 Midwestern states could supply four times the current US demand (Grubb and Meyer, 1993).

We recognize that the problem of overlapping federal, state, and local jurisdictions compounded by the lack of regulatory incentive to build new lines in restructured electricity markets makes transmission line construction a very difficult and uncertain prospect in the US. This analysis ignores these near-term regulatory issues, and only considers the construction and material costs to build such long distance transmission lines in the future.

Constructing long-distance transmission lines to utilize the best wind resources also provides the opportunity to geographically disperse wind turbine arrays, thereby decreasing the intermittency of the aggregate wind energy system. Geographic dispersion of turbine arrays over sufficiently large areas on the order of 1000 km can increase the reliability of wind by averaging wind power over the scale of prevailing weather patterns. Kahn (1979) quantified the reliability benefit of geographically dispersed wind turbine arrays using California data. While the main thesis of the paper



Power Class	Wind Power (W/m² at 50m)	Speed (m/s)	Capacity Factor (%)	Average Cost (¢/kWh)
1	<200	<5.6	10	8.35
2	200-300	5.6-6.4	18	4.78
3	300-400	6.4-7.0	24	3.66
4	400-500	7.0-7.5	28	3.19
5	500-600	7.5-8.0	32	2.83
6	600-800	8.0-8.8	38	2.43
7	>800	>8.8	45	2.10

Map adapted from Elliot et al (1986)

Fig. 1. Model geometry and map of US wind potential. The table relates wind class to average cost using the optimistic cost parameters for future wind in Table 1. The capacity factors were estimated from McGowan (2000). The map also shows the geometric configuration of wind sites used in the optimization model presented in Section 3. Sites were selected for sufficient geographic diversity to span synoptic scale weather patterns across the Great Plains. Chicago, IL is the demand center being served.

is that the geographical dispersal of turbine arrays improves the aggregate reliability, the ratio of ELCC (effective load carrying capability) to wind turbine capacity indicates that the diversity benefit reaches diminishing returns when the model is extended beyond Northern California to the entire Pacific region (Kahn, 1979). More recently, the diversity benefit was demonstrated by comparing the average wind power output across 1 (in Kansas), 3 (across Kansas), and 8 (spanning Kansas, New Mexico, Texas, and Oklahoma) wind sites (Archer and Jacobson, 2003).

3. Model

The purpose of this optimization model is twofold: (i) to provide an economic characterization of large-scale wind when intermittency and remoteness cannot be ignored, and (ii) to determine the cost of carbon mitigation of wind at different levels of penetration by constructing supply curves. The greenfield model minimizes the averaged delivered electricity cost by adjusting geographically dispersed wind turbine arrays, a storage system, and backup gas turbines to meet a time-varying load under a carbon tax.

Early versions of the model included coal, but it is driven out of the generating mix at a carbon tax of $\sim$ 50\$/tC while wind does not enter until carbon taxes exceed 100\$/tC. As a result, there is no direct tradeoff between wind and coal capacity under a carbon tax in our greenfield system. Although coal with CCS and nuclear are both capable of supplying baseload power with near-zero carbon emissions, these technologies were not included in our analysis both for simplicity, and because their slow response to supply and demand variability (slow ramp rates) make dispatch in a wind-dominated system difficult and expensive. The absence of these technologies in our model highlights an important assumption: coal and other technologies that cannot ramp quickly to compensate changes in supply or demand will be of little value in a wind-dominated system. In our view, if wind is employed as a strategy to achieve deep reductions in electric sector emissions, then it will be competing with gas turbines and other technologies capable of fast ramping and low emissions. The rapid growth in gas turbine capacity is likely to continue as a cost-effective near-term measure to curb carbon emissions, thereby supplanting older coal capacity and making the economics increasingly attractive for wind.

3.1. Structure

The model includes 5 wind sites (Fig. 1). The simulated wind power time series from the 5 sites serve as the cornerstone of the optimization, determining how

Table 1
Cost and efficiency parameters used in the optimization model

	GT	GTCC	Wind	HVDC	CAES
Efficiency (%)	35	55		85[a]	86
Capital cost ($/kW)	350	450	600	530,000[b]/100	400[c]/0.33
Fuel cost ($/GJ)	4	4			4
Fixed O&M ($/kW yr)	7	15	10		10
Variable O&M ($/kWh)	0.0005	0.0005	0.002		0.004

Gas turbine costs are based on Johnson and Keith (2004). Wind costs are based on McGowan (2000), with a lower capital cost of 600$/kW, likely achievable in the next two decades. The CAES cost and efficiency estimates are based on Cavallo (1995), EPRI/DOE (2003), as well as conversations with members of industry, then projected a couple decades out. All capital costs are evaluated at a 10% discount rate and 20 year lifetime.

[a]The transmission line losses were calculated each hour according to the formula: $P_{\text{out}} = P_{\text{in}}(1 - T_{\text{eff}} \times (P_{\text{in}}/T_{\text{cap}}))$. The transmission line efficiency, T_{eff}, is 85% at the thermal limit.

[b]$530,000/mile for a 408 kV DC-bipole transmission line with a thermal line rating of 1934 MW; $100/thru kW represents the substation cost for the HVDC line (Hauth et al., 1997). The capital cost ($/kW) for each line is given by

$$\text{Capital cost}\left(\frac{\$}{\text{kW}}\right) = \text{Capital cost}\left(\frac{\$}{\text{mile}}\right) \times \frac{1}{\text{Thermal line rating}}\left(\frac{1}{\text{kW}}\right) \times \text{Line length(miles)} + \text{Substation cost}\left(\frac{\$}{\text{kW}}\right)$$

Because each transmission line in the model had a different length, this calculation resulted in five different transmission line capital costs.

[c]The cost of the turbomachinery components is 300$/kW of expander capacity, with an estimated balance of plant cost of 100$/kW. In cases where the ratio of compressor/expander capacity is not 1, the cost of compressor capacity is 150$/kW and the cost of expander capacity is 150$/kW. 0.33$/kWh$_e$ represents the cost to develop an underground storage reservoir. The reservoir cost is a rough composite between the cost of using an aquifer, 0.10$/kWh$_e$ (our estimate) and a solution mined salt cavern, 1$/kWh$_e$ (Holdren et al., 1999).

much, where and at what carbon tax wind capacity is installed. The other capacities are optimized along with wind to meet the model constraint that total energy supplied equals total energy demanded, such that the cost of electricity over the course of the simulation is minimized.

The baseline model contains 13 decision variables, as indicated by the number in parenthesis in the following list:

- Wind capacity at each of the five sites (5).
- Transmission line capacities between sites Fargo, Helena, Amarillo, Cheyenne and Sioux City (4).
- Transmission line capacity between site Sioux City and Chicago (1).
- Capacity of the compressor/turboexpander associated with the storage system located at Sioux City (1).
- GT and GTCC capacities located at the Chicago demand center (2).

The parameter values used for capital costs, natural gas turbine efficiencies, and natural gas costs in the model are presented in Table 1. Sensitivity analysis of natural gas cost as well as wind and storage capital costs were performed.

3.2. Technology assumptions

The model includes both single-cycle gas turbines (GT) and combined-cycle gas turbines (GTCC), and assumes a baseline cost of 4$/GJ for natural gas, consistent with the 20-year projection in the Reference Scenario of the US Energy Information Administration's (EIA) *Annual Energy Outlook* (EIA, 2003). See Table 1. Because natural gas is the only source of carbon emissions in the system, the cost of natural gas and the carbon tax are commensurate: a natural gas cost of 6$/GJ instead of 4$/GJ would reduce the carbon taxes in the model by ~ 150$/tC. Our greenfield model simplifies the scheduling problem by only utilizing gas turbines and wind to meet load. Because the simulated wind power is an hourly time series, we do not have enough time resolution to quantify the cost of AGC or intra-hour balancing. However, gas turbines have fast ramp rates suitable for AGC and load-following. As such, our model assumes that the installed gas turbines are technically capable of resolving the minute-to-minute and intrahour balancing problem, but these balancing costs are not calculated.

The capital costs of storage can roughly be divided between power- and storage-specific capital costs. The former is the cost to generate electricity with a storage technology, and the latter is cost to develop a storage reservoir. Compressed air energy storage (CAES) and pumped hydro are the only storage technologies that offer sufficiently low storage-specific capital costs suitable for use in conjunction with large wind farms. Because pumped hydro requires two bodies of water at different elevations located in close proximity to each other, its application is limited. By contrast CAES is broadly applicable since roughly 80% of the land in the US has suitable geology, including solution-mined salt caverns, depleted gas reservoirs, hard rock caverns, aquifers, or abandoned mines (Cavallo, 1995). While several storage technologies such as batteries, capacitors, flywheels, and superconducting magnetic energy storage exist, either their cost per kWh makes them prohibitively expensive in large-scale applications or they are specifically designed for intra-hour load following.

To first order, a CAES system is simply a gas turbine in which the compressor and expander are disconnected, and high-pressure air produced by the compressor is stored in an underground reservoir at roughly 80 times atmospheric pressure. When connected to a wind farm, excess wind-generated electricity that exceeds the transmission line capacity can be used to run the compressor and store air at high pressure. When lulls in the wind require electricity from the CAES system, compressed air is released from the storage reservoir, heated through a recuperator, mixed with natural gas, and then the air–gas mixture is burned in the turboexpander. In a simple-cycle gas turbine, approximately $\frac{1}{2}$ to $\frac{2}{3}$ of the power produced by the turbine is diverted to run the compressor. As such, the heat rate for a simple-cycle gas turbine is roughly 9750 Btu/kWh. For comparison, the specific CAES system design reported by Desai et al. (2003) has a heat rate of 4300 Btu/kWh. The advantage of CAES is that it burns natural gas more efficiently by precompressing air with excess wind-generated electricity. However, the functionality of CAES systems is limited by the size of the reservoir, and the installed compressor and expander capacities.

Only two compressed air energy storage (CAES) facilities are in operation today. The first was constructed in Huntorf, Germany in 1978 with a capacity of 290 MW and 4 h of storage, and the second was built in McIntosh, AL in 1991 with a capacity of 110 MW and a storage time of 26 h (Schoenung, 1996). A third is being constructed in Norton, OH with an ultimate capacity of 2700 MW to be achieved by adding 300 MW units incrementally (Borroughs and Bauer, 2001). When completed the Norton CAES facility will be able to run at full capacity for 16 h (Baxter and Makansi, 2003).

The model is allowed to construct a single CAES facility at the Sioux City, IA site. The CAES system was placed at the central wind site rather than the demand center because it makes more efficient use of the transmission infrastructure.

The economic performance of CAES depends strongly on the configuration of the storage system. For the model, we developed a partially optimized system that focuses on displacing gas turbine capacity. If the compressor capacity or the storage reservoir are too small, or if the expander capacity is too large, then the storage unit will dispatch energy at a faster rate than it receives excess wind energy and reserves will quickly be depleted. If this occurs, CAES will not be able to displace GTCC capacity, and the carbon tax at which CAES enters the model will be very high because the total cost of CAES must be lower the marginal cost of GTCC. To ensure that CAES operates optimally in the model by displacing gas capacity, we performed a parametric analysis of two important features of a CAES system: (1) the storage lifetime, which represents the amount of time the CAES facility can run continuously at full output if the storage reservoir is full, and (2) the ratio of compressor/expander capacity in the CAES system, which allows the compressor and expander capacities to optimize to different values. This latter parameter is important because it allows the storage system to absorb more energy than it can release at a given time, which means that CAES will not deplete the storage reservoir faster than it can be filled. Optimal parameter values were determined by using the method described in Section 4.

Long-distance electricity transmission will be a critical component in the development of large-scale wind, particularly for the geographic dispersal of wind turbines to work as a means of increasing reliability. To span the several hundred miles separating Great Plains wind energy from distant demand centers, high voltage direct current (HVDC) lines are more cost-effective than the equivalent three-phase HVAC lines. Assuming the same transmitted power, DC bipole line losses including skin effects and core losses are typically 65–73% of the equivalent 3-phase AC line (Hauth et al., 1997). Smaller DC line losses must be balanced by the higher capital cost and cost of losses associated with the DC to AC substations. Thus there is a break-even distance beyond which DC becomes more cost effective than AC, on the order of 100–400 miles depending on the specific configuration (Hauth et al., 1997). It should be noted that HVDC technology is not just theory—there are roughly 35,000 MW of HVDC transmission line capacity installed worldwide (Rudervall et al.). See Table 1 for details on the capital cost formulation used in the model.

Finally, we assume that the problems of remoteness and intermittency matter on a relative scale rather than an absolute. For example, constructing a remotely located 5 GW windfarm connected to a 10 GW grid poses the same basic problem as constructing a remotely located 50 GW windfarm connected to a 100 GW grid. Because supply must meet demand in real-time, addressing the intermittency problem from wind on a small-scale poses the same basic challenges as wind on a large-scale, provided that wind constitutes a significant fraction of supply in either case. However, the choice of transmission line limits the scale independence assumption. The optimization model utilizes HVDC lines to tie the wind farms to the demand center. These lines typically have large capacities in the range of 1–5 GW, and would only be constructed to transmit power of this magnitude. As such, the economic results generated by the model are roughly scale-independent for windfarms of a few GW capacity or more.

3.3. Wind data and site geometry

Hourly wind data for each wind site in Fig. 1 was obtained from the National Climatic Data Center (NCDC). NCDC makes available hourly wind recordings since July 1, 1996 from Weather Bureau Army–-Navy (WBAN) stations. Because the WBAN station data is recorded at ground level, the wind speed time series had to be scaled to represent wind speeds at higher altitudes. Although power law and logarithmic extrapolation are often used to estimate wind speeds at higher altitudes, these techniques ignore stability corrections, whereby winds are more constant with fewer periods of calm at standard turbine hub heights of 50–80 m (Grubb and Meyer, 1993). Although the work by Archer and Jacobson (2003) provides a noteworthy methodological improvement to the standard extrapolation techniques, it is quite data intensive. For simplicity, the wind speeds were scaled such that the resultant wind turbine capacity factors were close to 35%: a realistic value for wind turbines with a hub height of 80 m. Scaling the wind speed time series such that the mean in each case was 8 m/s resulted in capacity factors ranging from 32% to 35%. Our simplified scaling does not aim to provide the most accurate extrapolation of wind speeds, but rather to get the capacity factors and correlations between wind sites right, since they are the key factors that determine average cost.

The wind sites in the model were chosen for strong wind resources with a wide spatial distribution spanning the Great Plains in order to test the benefit of geographic site diversity. The specific towns we have chosen are not meant to represent the exact location of wind farms, rather, wind sites were chosen based on the location of WBAN stations that are near suitable areas of wind class 4 or 5 land. The model utilizes 5 years of simulated wind power, 1997–2001, to account for potential inter-annual variability in wind speed and correlation. Wind turbine power output was simulated by running the scaled wind speed time series through a parametrized wind power output curve for a Vestas 1.75 MW turbine.

To represent a time-varying load, recorded hourly PJM loads from 1997 to 2001 were used to represent Chicago demand. The PJM data is readily available, and serves as a reasonable proxy for Chicago demand since most load centers exhibit the same basic diurnal and seasonal fluctuations.

3.4. Results

At each carbon tax the optimization model calculates three quantities: (i) the optimal wind, transmission, storage, and gas turbine capacities, (ii) the fractional carbon emissions reductions, and (iii) the average cost per kWh. The baseline case represents the model results at zero carbon tax.

Fig. 2A represents the optimal wind, transmission, GTCC, GT, and CAES capacities as a function of carbon tax when the model is restricted to one wind site. Wind appears at a carbon tax of 140$/tC, a value that can be verified analytically. Because supply must meet demand each hour, there must be enough gas capacity (GT or GTCC) installed to meet demand when the wind farms are not producing electricity. As such, wind enters the system when the combined cost of the wind farm and transmission line is less than the marginal cost of the gas turbines (cost of gas, carbon tax, and variable O&M). At a carbon tax of 500$/tC, CAES enters the model. The CAES curve in Fig. 2 denotes turboexpander capacity, which represents the maximum power the CAES system can generate each hour.

Fig. 2B represents the optimal capacities when the model can optimize wind capacity across all 5 wind sites. At the highest carbon taxes, wind energy is serving roughly 70% of the electricity demand. At a carbon tax of 140$/tC, the model begins installing wind capacity at the Sioux City, IA site, as in the 1-site case. This is expected since the Sioux City site is closest to Chicago, and minimizes the investment in transmission. At a carbon tax of 280$/tC, the model installs wind capacity at the Cheyenne, WY and Fargo, ND sites. At a carbon tax of 300$/tC, wind capacity is also constructed at the Havre, MT and Amarillo, TX sites. This result suggests that at sufficiently high carbon taxes, the economic benefit of utilizing distributed wind sites with less correlated winds outweighs the cost of the longer HVDC transmission lines. As the carbon tax increases, wind is serving a larger fraction of demand and backup capacity is needed less often. As a result, GT capacity, with lower capital costs but higher variable costs, exceeds GTCC capacity at carbon taxes greater than 600$/tC.

In contrast to Fig. 2A, note that no CAES capacity is installed in Fig. 2B. This represents a key result of our analysis: there is a tradeoff between wind site diversity and storage. The use of geographically distributed wind sites mitigates the intermittency problem by increasing the aggregate level of wind power output, thereby limiting the economic benefit of storage.

In Figs. 2A and B, the combined GTCC, GT, and CAES capacities are equal to the maximum load across all carbon taxes, suggesting the coincidence of peak demand with little or no wind power output. In fact, there are 43 h in 6 years in which the power output across all five wind sites is zero. If all 5 wind power time series are averaged together with equal weighting, the correlation, r, between wind power and load over all 5 years is 14%.

To test the benefit of geographic site diversity, the model was run under five different scenarios, where each

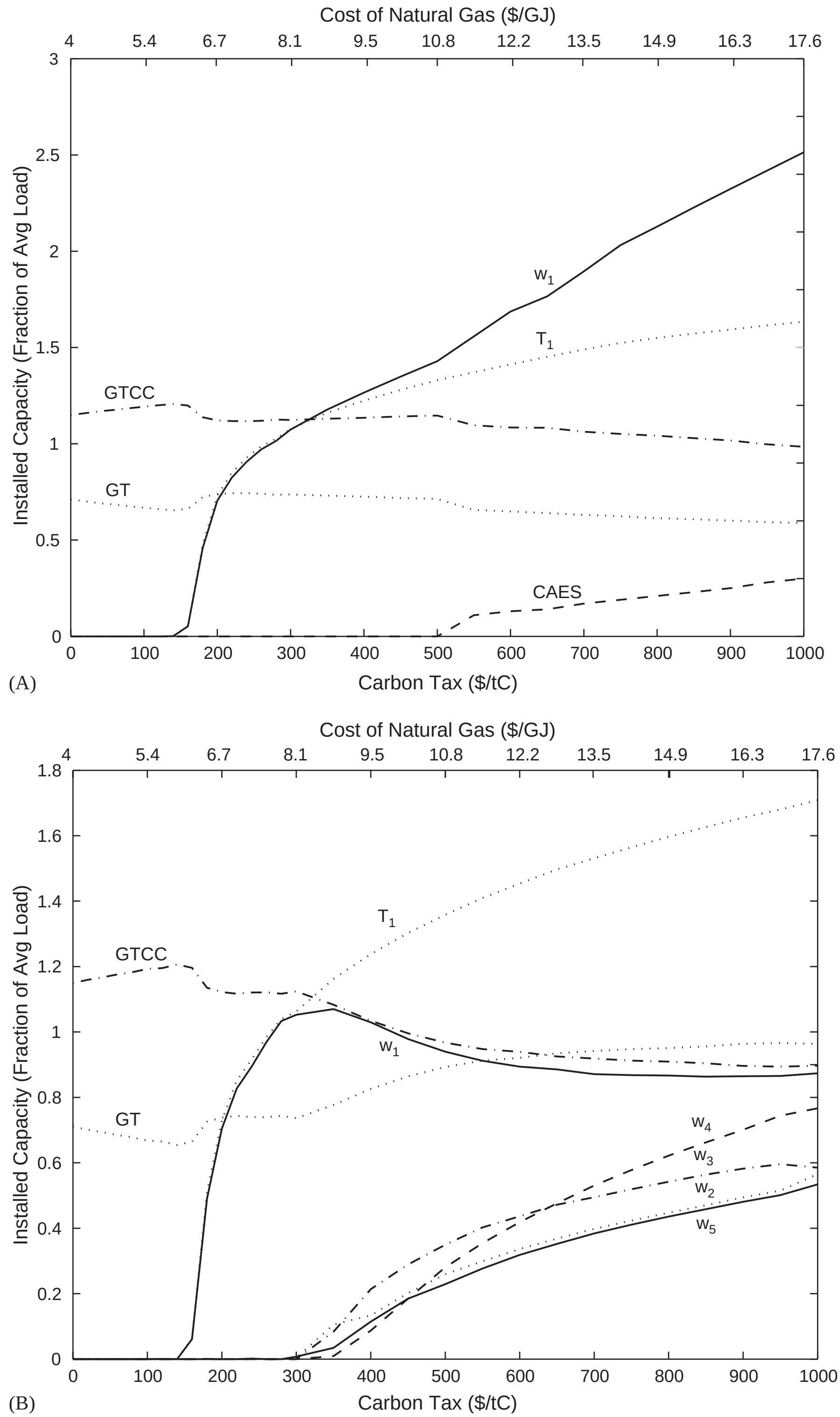


Fig. 2. Optimal capacities as a function of carbon tax. The effective cost of natural gas (fuel cost + carbon tax) is given along the top horizontal axis. As such, this plot can also be interpreted as a sensitivity analysis of natural gas cost, where adding 2$/GJ to the baseline natural gas cost would reduce the carbon taxes in the model by ~ 150$/tC. The tuned parameters for CAES determined in Section 4 were used. (A) 1 wind site in the model. (B) 5 wind sites in the model. In (B), the wind sites are w_1 = Sioux City, IA; w_2 = Fargo, ND; w_3 = Havre, MT; w_4 = Amarillo, TX; and w_5 = Cheyenne, WY.

scenario provided a different number of wind sites available to the optimization. For each scenario, $n \in \{1, \ldots, 5\}$, all combinations of n wind sites were simulated, and, for each n, the combination that yielded the lowest cost at a 25% reduction in emissions was used in plotting the five curves in Figs. 3 and 4. In Fig. 3, the

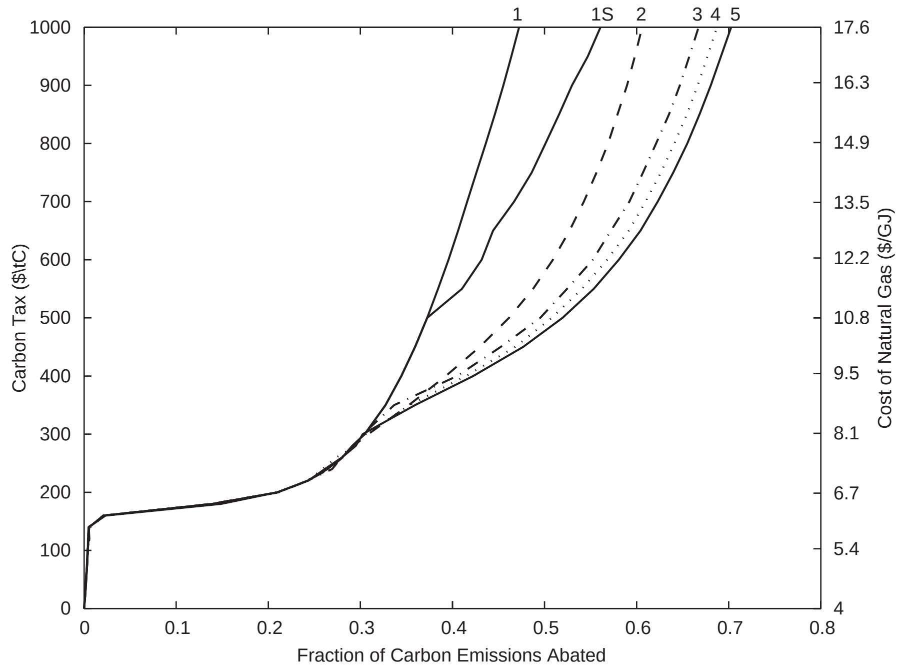


Fig. 3. Marginal cost of carbon mitigation as a function of the fractional reduction in emissions from the baseline scenario at zero carbon tax. The number above each curve represents the number of wind sites used in the model run. Because storage becomes cost-effective in the model run with 1 wind site, the curves representing wind with storage ('1S') and without storage ('1') are both shown for comparative purposes. Adding wind sites to the model increases the achievable carbon reductions. Because gas turbine utilization is directly traded for wind utilization as the carbon tax increases, the level of carbon abatement can also be interpreted as the fraction of wind energy serving demand. All five scenarios demonstrate declining marginal reductions in carbon emissions as the carbon tax increases above 500$/tC, which is due to the inherent intermittency of the wind, which always requires some amount of backup gas turbine capacity to ensure that supply meets demand each hour.

fraction of carbon emissions reduction is higher at a given carbon tax with more wind sites, for example, a carbon tax of 500$/tC produces a 37% reduction when $n = 1$, compared to a 52% reduction for $n = 5$. The benefits of wind site diversity are also demonstrated in Fig. 4, where the average cost at each level of carbon emissions abatement is inversely proportional to the number of wind sites used by the model; for example, to achieve a 50% reduction in carbon emissions with wind, the average cost is 5.6 ¢/kWh for $n = 1$, and 5.1 ¢/kWh for $n = 5$.

Fig. 3 demonstrates the fractional emissions reductions as a function of carbon tax. In all five scenarios, the results exhibit declining marginal reductions in carbon emissions as the carbon tax is increased beyond 500$/tC. The decline occurs because as wind capacity increases with the carbon tax, a significant amount of wind is wasted as the supply of wind energy exceeds demand. While adding additional wind sites reduces the number of hours with low or zero wind power output and expands the carbon reductions frontier, there is still an effective limit imposed by intermittency. Regardless of how much wind capacity is built, there are still periods when the wind does not blow and the backup gas turbine capacity must be utilized to meet the load.

Rather than imposing a carbon tax, the model can be run by imposing a constraint on the allowable carbon emissions. In this case, the model computes the minimum cost of supplying electricity to meet the carbon constraint. Fig. 4 represents a key model result: average cost (without the carbon tax) as a function of fractional carbon emissions reductions. There is a tradeoff between wind and gas turbine utilization as a function of carbon tax, so the fraction of carbon emissions abatement can also be read roughly as the fraction of wind-generated electricity serving demand. The average cost of electricity supplied by GTCC and GT is 3.95 ¢/kWh in the base case. The average cost rises as the level of wind capacity increases with the carbon constraint.

The increasing costs of wind can be understood as follows. Neglecting intermittency, the *average cost* of wind power delivered to the load center at Chicago from the Sioux City site is 4.1 ¢/kWh including transmission line capacity and transmission losses, just a few percent larger than the average cost of electricity in the all-gas baseline. The 'CoW1' line in wind Fig. 4 is constructed to intersect the right-hand axis, which corresponds to the hypothetical emission-free system at this average cost. The line therefore indicates the costs that would arise if intermittency could be neglected.

The line labeled 'CoW2' is tangent to the cost curve at zero carbon tax; it therefore includes the cost to have gas turbines serve as reserve capacity to mitigate wind

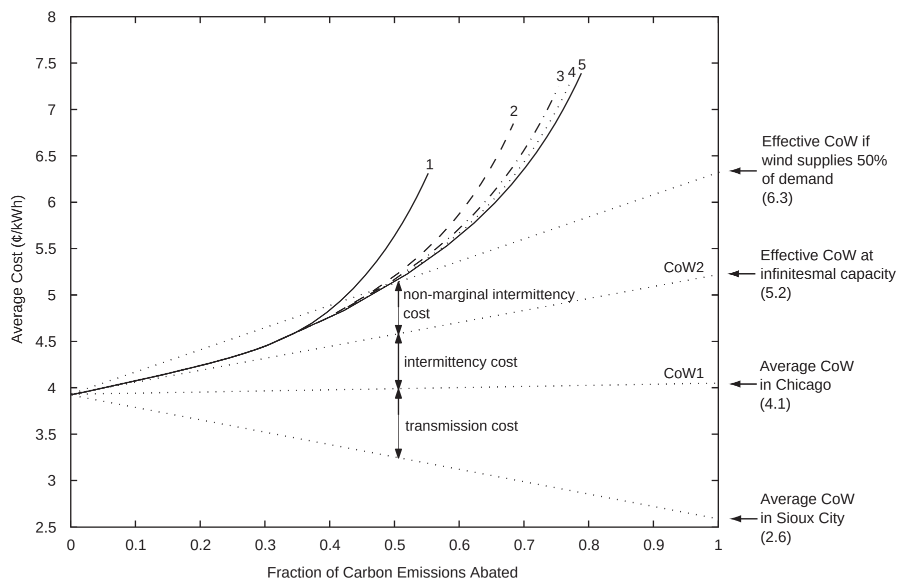


Fig. 4. The average cost of electricity as a function of the fractional reduction in emissions. The number above each curve represents the number of wind sites used in the model run. The labels on the right-hand side refer to the average cost of dispatchable wind (CoW) under various assumptions. The line labeled 'CoW1' is the cost of using wind to mitigate carbon emissions, accounting for the cost of the transmission line and transmission losses, but assuming wind is perfectly dispatchable. The line labeled 'CoW2' is tangent to the cost curve at zero carbon tax and includes the cost to have gas turbines serve as reserve capacity to mitigate wind intermittency. Therefore, 'CoW2–CoW1' represents the cost of using gas turbines as reserve capacity to mitigate intermittency. The costs above 'CoW2' are also due to intermittency: each marginal addition of wind capacity produces a lower marginal reduction in emissions.

intermittency. The difference 'CoW2-CoW1' represents the cost of intermittency if these costs were independent of the amount of wind capacity.

The costs above 'CoW2' arise because the addition of wind capacity produces marginally declining reductions in emissions because more of the wind power must be wasted as supply exceeds demand (see Figs. 3 and 4).

When use of all wind sites is allowed ($n = 5$), the additional cost of using wind to reduce carbon emissions by 50% is 1.2¢/kWh, with 0.6¢/kWh attributable to the cost of managing intermittency with backup capacity and an additional 0.6¢/kWh attributable to the declining cost effectiveness of wind when wind capacity is large compared to demand. With $n = 1$, the added cost due to declining cost-effectiveness rises to 1.1¢/kWh. Finally, extrapolating the cost of wind at a 50% emissions reduction (in the 5-site case) to the right-hand axis indicates that the effective cost of dispatchable wind energy serving 50% of demand is 6.3¢/kWh.

4. Exploring the benefits of CAES

The absence of CAES capacity in Fig. 2B and the utilization of CAES only at high carbon taxes in Fig. 2A is an intuitively surprising result. Residual emissions generated by the CAES system handicap its performance under a carbon tax, such that CAES does not compete effectively with GT and GTCC capacity. To scrutinize CAES performance under a variety of assumptions, a reduced form optimization model was constructed. Rather than embedding a simulation of wind power within the optimization, the reduced-form model depends on four functions: (1) the fraction of load served by wind as a function of installed wind capacity, FLS, (2) the minimum power supplied by wind, MPS, (3) the derivative of FLS with respect to storage expander capacity, FLS′, and (4) the derivative of MPS with respect to storage capacity, MPS′. See Fig. 5. All four are functions of installed wind capacity and are evaluated at zero storage capacity since our objective is to study the value of storage at the margin.

In this model, one wind site competes directly with GTCC as a function of carbon tax, assuming constant load and 5 years of wind power simulation from the Sioux City, IA wind site. Neglecting storage, the cost is given by

$$wW_C + G_C(1 - \mathrm{MPS}(w)) + W_V\,\mathrm{FLS}(w) + G_V(1 - \mathrm{FLS}(w)),$$

where W represents wind costs, G represents GTCC costs, the subscript 'C' denotes capital costs and 'V' denotes variable costs. In addition, w represents wind capacity. The costs are given in Table 1.

Adding storage at the margin will change the value of the FLS and MPS functions. We estimate the marginal cost of storage by adding a small amount of storage

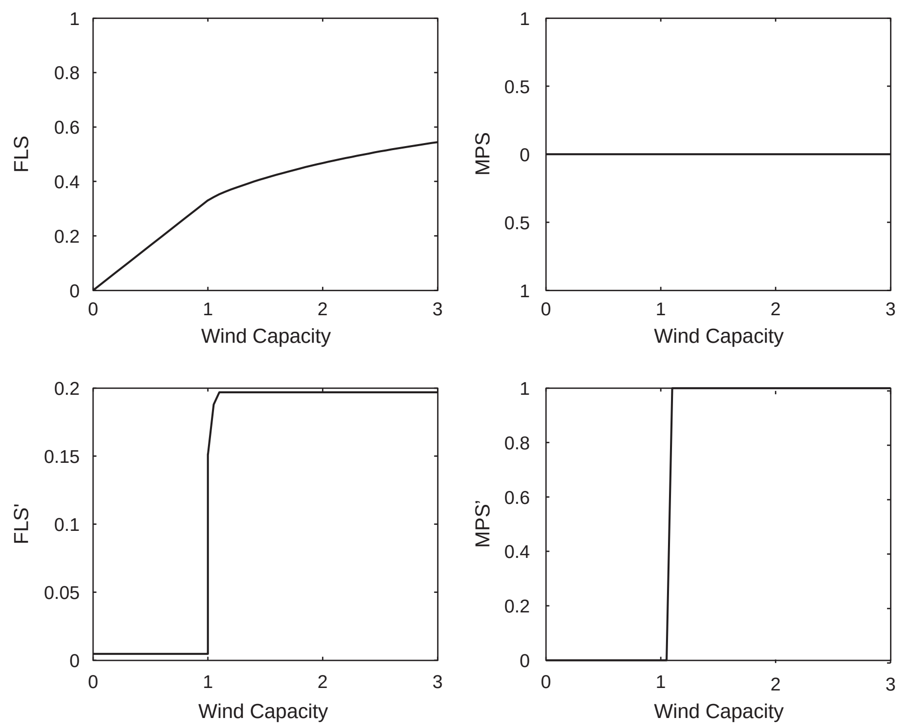


Fig. 5. The four functions used in the reduced-form model. The functions were obtained by stepping the wind capacity at the Sioux City, IA site and running the wind power vector through the storage algorithm. The storage parameters are optimally tuned such that CAES becomes cheaper than GTCC at the lowest possible carbon tax. In this case, the storage lifetime is 550 h and the ratio of compressor/expander capacity is 1.2, and CAES becomes cost-effective at a carbon tax of 335\$/tC.

(expander) capacity, recalculating the values of FLS and MPS as a function of wind capacity in the reduced-form model, and calculating the numerical derivatives FLS′ and MPS′. Adding storage will tend to increase FLS at a given level of wind capacity, and push MPS to a nonzero value if energy from storage can always be dispatched to fill in hours with no wind power output. The marginal cost of storage can be expressed as

$$C' = -G_C\,\mathrm{MPS}' + \mathrm{FLS}'(S_V - G_V) + \mathrm{SP_C} + \mathrm{SS_C} S_T, \tag{1}$$

where $\mathrm{SS_C}$ represents the storage-specific capital cost to develop the underground reservoir, $\mathrm{SP_C}$ represents the power-specific capital cost for the storage turbomachinery components, and S_T is the length of time that CAES can run at full capacity. CAES becomes cost-effective when C' is less than zero; that is when the total cost of CAES is less than the displaced GTCC costs at a given carbon tax.

Because the economic performance CAES is sensitive to its configuration, we performed a parametric analysis of the storage lifetime and ratio of compressor/expander capacity using Eq. (1). The pair of parameters that make CAES more cost-effective than GTCC at the lowest carbon tax are considered optimal. With the costs given in Table 1, CAES becomes cost-effective at 335\$/tC, when the storage lifetime is 550 h and the ratio of compressor/expander capacity is 1.2. This result indicates that CAES operates more efficiently in this simple system when there is more compressor capacity than expander capacity, because a larger compressor can more effectively capture the excess wind energy. Table 2 demonstrates how the carbon tax at which CAES becomes cost-effective changes as the storage lifetime

Table 2
Carbon tax at which CAES and H_2 storage systems become cost-effective over GTCC, as a function of the storage lifetime and storage-specific capital cost

Storage lifetime (h)	Storage-specific capital cost (\$/kWh$_e$)			
	0.1	0.33	1	0.01 (H_2)
100	1000	1140	1170	910
500	410	410	730	770
1000	330	380	1780	730
1500	340	720	>2000	410
2000	280	1070	>2000	340
2500	280	1410	>2000	340

The storage-specific capital cost represents the cost to develop an underground storage reservoir. The low estimate (0.10\$/kWh$_e$) represents the cost to use an aquifer as the storage medium (our estimate), and the high estimate (1\$/kWh$_e$) represents the cost to develop a solution-mined salt cavern (Holdren et al., 1999). In the H_2 scenario, $\mathrm{SS_C} = 0.01$\$/kWh$_e$, based on Ogden (1999). The ratio of compressor/expander capacity was set to the tuned values for CAES and H_2, 1.2 and 2.5, respectively.

and storage-specific capital cost are varied, while holding the ratio of compressor/expander capacity constant at 1.2.

4.1. Cost comparison with an H_2 system

Because CAES is penalized by its residual carbon dioxide emissions, we decided to test the performance of an H_2 storage system, which does not produce carbon emissions. Excess wind can be used to run an electrolyzer to generate hydrogen, which can then be stored under pressure in a storage reservoir. When electricity is needed, the hydrogen is released from storage and burned in a combustion turbine. The cost to generate hydrogen from large-scale alkaline electrolysis is projected to be as low as 300$/kW at efficiencies of 70–85% (HHV), and the levelized cost to store H_2 underground (in the same formations as compressed air) is $2–$6/GJ (Ogden, 1999). It is also plausible to assume that combined-cycle H_2 turbines could operate at the costs and efficiency given for GTCC in Table 1 (Audus and Jackson, 2001). As such, an H_2 storage system could likely operate with a round-trip efficiency of roughly 40%.

As with CAES, a parametric analysis was performed to determine the optimal storage lifetime and ratio of electrolyzer/turbine capacity that allows the H_2 system to become cost-effective at the lowest carbon tax. An optimal H_2 storage system becomes cost-effective over GTCC at 343$/tC with a storage lifetime of 2500 h and an optimal ratio of electrolyzer/turbine capacity of 2.7. The tuned H_2 system requires significantly more storage reservoir capacity and more electrolyzer capacity than in the analogous CAES system for two reasons: (i) the H_2 system has an electricity output/input ratio of 0.4 compared with 1.5 for CAES, which means much more energy will be lost in the H_2 system, and (ii) the H_2 system does not incur fuel costs or a carbon tax penalty so more capital can be devoted to building additional storage capacity in order to make up for the energy lost through inefficiency.

The comparative economic performance of CAES and H_2 is given in Fig. 6, which plots the value of the cost derivative in Eq. (1) as a function of carbon tax. An unoptimized CAES system, in which the storage lifetime is 100 h and the compressor/expander ratio is 1, does not become cost-effective until a carbon tax of more than 1000$/tC. Varying the storage lifetime and compressor/expander ratio demonstrates that CAES performance can be dramatically improved when the parameters are tuned, making CAES cost-effective at 335$/tC. The first steep drop in the cost derivative near 260$/tC

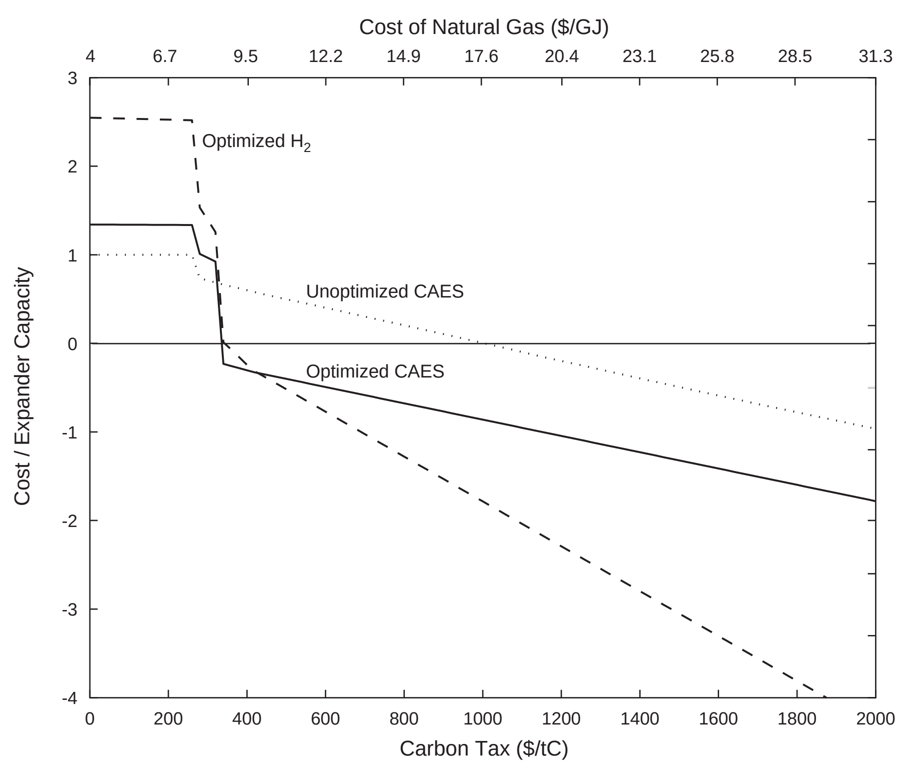


Fig. 6. Plot of C′, Eq. (1), as a function of carbon tax. The curves were normalized by the C′ of unoptimized CAES evaluated at zero carbon tax. Storage is more cost-effective than GTCC when the derivative crosses zero. CAES and H_2 become cost-effective at 335$/tC and 343$/tC, respectively, when the parameters are tuned. In the model run with optimized CAES, the storage lifetime is 550 h and the ratio of compressor/expander capacity is 1.2. In the model run with optimized H_2, the storage lifetime is 2500 h and the ratio of compressor/expander capacity is 2.7. Both CAES and H_2 with tuned parameters perform significantly better than the non-optimal CAES with a compressor/expander ratio of 1 and a lifetime of 100 h.

corresponds to the jump in FLS′ when wind capacity exceeds 1 (because excess wind fills the storage reservoir), and the second steep drop at 320\$/tC corresponds to the jump in MPS′ when CAES displaces GTCC capacity. In the unoptimized curve, there is no second steep drop because CAES does not displace GTCC capacity, so CAES only becomes cost-effective when its total costs are lower than the marginal costs GTCC. The H_2 system is the most expensive at zero carbon tax, but exhibits a dramatic decline in cost relative to GTCC because it is unaffected by the carbon tax, and becomes cost effective at 343\$/tC.

5. Conclusions

The model presented here allows us to estimate the cost of using large-scale wind to achieve deep cuts in CO_2 emissions by optimizing distributed wind sites, transmission lines, storage, and gas turbines to mitigate the problems posed by remoteness and intermittency. While the model is idealized, we can nevertheless draw several interesting conclusions about the use of large-scale wind.

First, assuming comparatively low costs for wind turbines and a low discount rate of 10%, the average cost of electricity in a gas/wind system in which wind supplies half of demand is of order 5 ¢/kWh including the cost of transmission and backup. Under our aggressive cost assumptions for wind, the average cost of wind at the remote site is 2.6 ¢/kWh, about 30% less than the cost of electricity in our all-gas system. If wind must supply half of demand, the costs arising from intermittency and the remote location of wind sites increase the effective cost of wind power by about 3.7 to 6.3 ¢/kWh, consistent with the estimates in DeCarolis and Keith (2001).

Second, even when the costs of intermittency and location are included, wind power is roughly competitive with costs of using other technologies, such as nuclear or coal with CCS, to achieve deep reductions in CO_2 emissions. For example, using similar economic assumptions to those employed here, Johnson and Keith (2004), found that the cost to reduce carbon emissions by 50% using a combination of coal to gas fuel switching and CCS was 1–2 ¢/kWh, with CCS entering at carbon taxes of 100\$/tC or less. Our results suggest that, even when it is required to supply more than half of demand, large-scale wind can be a competitive means of mitigating CO_2 emissions.

Third, the costs imposed by wind intermittency scale to very low levels of penetration, contradicting several studies that suggest there is a threshold, typically 10–20%, below which wind does not affect grid stability or impose substantial costs (e.g., Richardson and McNerney, 1993; EWEA, 2003). Such studies do not account for the cost resulting from a decrease in available system reserve and so neglect the decreased level of grid reliability, however small, stemming from intermittent wind. In contrast, we find that even small amounts of wind must be matched by additional gas capacity serving as system reserve, or reliability would be compromised.

Fourth, the economic benefit of expanding the spatial distribution of wind farms to reduce intermittency can exceed the costs of additional transmission infrastructure. Fig. 3 demonstrates that at carbon taxes greater than 280\$/tC, increasing the number of wind sites in the model increases the achievable level of carbon emissions abatement. Fig. 4 demonstrates that at a given level of carbon emissions abatement (without a carbon tax), increasing the number of wind sites in the model decreases the average cost of the system.

Fifth, there is a direct tradeoff between wind site diversity and storage. Spreading out wind farms reduces wind speed correlations, which mitigates the intermittency problem by smoothing out the aggregate wind power time series. Fig. 2B demonstrates that sufficient wind site diversity renders CAES economically uncompetitive, even at carbon taxes approaching 1000\$/tC, whereas with only a single wind site CAES is cost effective at 500\$/tC.

Sixth, CAES is less competitive than expected under a carbon tax: its residual carbon dioxide emissions do not allow it to compete effectively against gas turbines. In addition, Fig. 6 demonstrates that the economic performance of storage is sensitive to how well the storage parameters are tuned. Interestingly, both CAES and the H_2 system described in Section 4.1 exhibit similar economic performance, both becoming cheaper than GTCC near a carbon tax of 340\$/tC. CAES has lower capital costs and a higher roundtrip efficiency, but burns gas and incurs an economic penalty from the carbon tax. On the other hand, the H_2 system has significantly higher capital costs and a lower roundtrip efficiency, but does not require a natural gas and is not subject to the carbon tax. More generally, the storage analysis also indicates that a large-scale storage system that does not require the use of a fossil fuel (and has reasonable capital costs) could make a big contribution in a wind-dominated system.

Finally, the use of GT and GTCC as backup are a crucial part of our large-scale wind system, particularly in the scenario with five wind sites. As the level of wind increases in the 5-site system, the sum of GTCC and GT capacities remains constant and equal to the maximum load, which suggests the coincidence in our data set between peak demand and no wind power output. At high levels of wind penetration, the gas turbines effectively act as capacity reserve that ramp to complement the time-varying wind. When wind serves upwards of 60% of demand, the model chooses to install more

GT than GTCC capacity because of the lower rates of gas utilization.

Coal was not included in our greenfield model because it exists in a different carbon tax regime than wind, and is eliminated at carbon taxes exceeding 50$/tC. Even if existing coal capacity were included in the model, it would be very expensive to run at high carbon taxes, and furthermore, at high levels of wind penetration coal ramps too slowly to be a useful complement to intermittent wind.

In summary, the cost of wind serving more than a third of demand, accounting for the remoteness and intermittency of wind resources, is similar to the cost of other carbon mitigating technologies in the electricity sector. While we do not discount the ability of other technologies to compete effectively with wind, we assert that wind is a serious option for electricity generation in a carbon constrained world.

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