Energy Policy 68 (2014) 123–131

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

The role of energy storage in accessing remote wind resources in the Midwest

Julian Lamy*, Inês L. Azevedo, Paulina Jaramillo

Department of Engineering & Public Policy, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, PA 15213, United States

HIGHLIGHTS

- We evaluate the break-even cost of energy storage to replace transmission.
- We focus on a wind farm in North Dakota that must deliver power to Illinois.
- Energy storage capital costs must be less than $100/kW h.
- Transmission capital costs must be greater than $600/MW-km.

ARTICLE INFO

Article history:
Received 5 June 2013
Received in revised form
9 January 2014
Accepted 10 January 2014
Available online 16 February 2014

Keywords:
Wind power
Transmission
Energy storage

ABSTRACT

Replacing current generation with wind energy would help reduce the emissions associated with fossil fuel electricity generation. However, integrating wind into the electricity grid is not without cost. Wind power output is highly variable and average capacity factors from wind farms are often much lower than conventional generators. Further, the best wind resources with highest capacity factors are often located far away from load centers and accessing them therefore requires transmission investments. Energy storage capacity could be an alternative to some of the required transmission investment, thereby reducing capital costs for accessing remote wind farms. This work focuses on the trade-offs between energy storage and transmission. In a case study of a 200 MW wind farm in North Dakota to deliver power to Illinois, we estimate the size of transmission and energy storage capacity that yields the lowest average cost of generating and delivering electricity ($/MW h) from this farm. We find that transmission costs must be at least $600/MW-km and energy storage must cost at most $100/kW h in order for this application of energy storage to be economical.

1. Introduction

There is growing concern in the United States about how to reduce the emissions of criteria air pollutants and greenhouse gases (GHG) associated with fossil fuel electricity generation. Replacing current generation with renewable energy could provide part of the solution since most renewable technologies do not produce emissions and provide long-term sustainable sources of energy. In 2008, a report by the U.S. Department of Energy (U.S. Department of Energy (DOE), 2008) suggested that wind energy could provide 20% of electricity generation in the U.S. by 2030. Federal and local governments in the United States are promoting an increase in renewable capacity with incentives such as the federal production tax credit for wind power. In addition, 29 states and Washington, DC have implemented Renewable Portfolio Standards (RPS) calling for up to 40% of generation coming from qualifying renewable resources (Database of State Incentives for Renewables & Efficiency (DSIRE), 2013). It is expected that wind will be the largest contributor to these targets. However, in order to meet these ambitious targets, many questions about integrating wind resources must be answered.

Many studies have analyzed the challenges with integrating wind into the electricity grid in the United States, and most of that work has focused on the variability of wind power. For example Jacobson and Delucchi (2011a,2011b) claim that adding large amount of renewable generation to the world's electricity mix can provide energy at costs equal to current costs. Others such as Trainer (2011) argue that when the true cost of power variability is accounted for, renewable integration, especially at such a large scale, does indeed incur nontrivial increases in energy costs. DeCarolis and Keith (2006) showed that increasing wind power to serve 50% of demand adds about $10–20/MW h to the cost of electricity due to the intermittency of wind power output and the

* Corresponding author. Tel.: +14122682670; fax: +14122683757.
E-mail addresses: jlamy@andrew.cmu.edu (J. Lamy), iazevedo@cmu.edu (I.L. Azevedo), pjaramil@andrew.cmu.edu (P. Jaramillo).

0301-4215/$ - see front matter © 2014 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.enpol.2014.01.008

increased capital cost incurred to build supporting transmission capacity. Lueken et al. (2012) analyzed the variability of 20 wind farms in the Electric Reliability Council of Texas (ERCOT) over one year and concluded that costs due to variability are on average $4/MW h, when using ancillary service costs in California as an estimate for variability cost.

There has also been considerable attention recently to the application of energy storage to integrate wind power and handle variability concerns. Greenblatt et al. (2007) and Hittinger et al. (2010) explored how wind could be used as baseload power when coupled with energy storage capacity and natural gas generation. Paul Denholm et al. (2005) performed a similar analysis that concluded that wind could have as high as 80% capacity factor (similar to coal and nuclear generators) when coupled with Compressed Air Energy Storage (CAES).

Other papers have focused on the profitability of using energy storage in current energy markets. Fertig and Apt (2011) analyzed the economics of a hypothetical integrated CAES-wind farm system in Texas that takes advantage of price arbitrage opportunities. They found that in most scenarios, the unit was unprofitable when participating in real-time energy markets in ERCOT. Similarly, using a stochastic dynamic programming model that accounts for uncertainty in hourly prices and wind power, Mauch et al. (2012) found that a wind-CAES system participating in day-ahead markets would not be profitable, even with a carbon price of $20 to $50 per tonne CO_2.

In addition to power variability, there are also challenges with economically accessing wind power. Many of the highest capacity factor wind resources are located in areas that are far away from load centers and therefore require large transmission investments. The alternative to accessing these distant resources is to build local wind farms that often have lower wind potential but require lower transmission investments. Hoppock and Patiño-Echeverri (2010) studied the problem of whether it is more economical to integrate wind (up to 10 TW h of wind generation) in local or remote locations to comply with the Illinois RPS and concluded that local resources in Illinois provide the least costly investment. They used the average annual capacity factor of different sites at varying distances in the Midwest to estimate the average cost of each site ($/MW h), including the costs of transmission needed to access distant farms. They found that the major cost-driver that prevents remote wind development is transmission costs, which ranged from $1200/MW-km to $4200/MW-km in their analysis.

In addition to the transmission costs assumed by Hoppock and Patiño-Echeverri (2010), there is a wide range of cost estimates used throughout the literature. In their economic analysis of CAES in Texas, Fertig and Apt (2011) developed a transmission cost model using historical data. This model was developed using actual transmission costs that ranged from $200/MW-km to $900/MW-km. Similarly, Denholm and Sioshansi, 2009 reported transmission costs ranging from $100/MW-km to 1300/MW-km. Further, as highlighted in Fischlein et al. (2013), transmission investments will require considerable coordination among local and federal government. Issues such as siting, line planning, and permitting are non-monetary costs that add complexity to building transmission projects. Careful treatment of the uncertainty in transmission costs is therefore important when modeling the economics of remote wind projects.

One solution to reducing transmission costs associated with accessing remote wind is to reduce the capacity of the transmission line available to the remote farm. Because wind farms rarely generate at full capacity – average capacity factors range between 25% and 50% for farms within the Eastern Interconnect according to the Eastern Wind Interconnection and Transmission Study (Database of the Eastern Wind Interconnection Study (EWITS), 2012) produced by the National Renewable Energy Lab (NREL) – the optimal transmission capacity to access one farm is less than the farm′s full capacity. Pattanariyankool and Lave (2010) showed that the optimal transmission capacity needed to access a remote farm ranges from 70% to 80% of the farm′s nameplate capacity. They assumed that the farm incurs capital cost of transmission per unit of capacity (MW) and therefore with less capacity, the project would save on costs. The caveat, however, is that during times that the farm generates more electricity than this transmission capacity, the operator would have to curtail power and forego revenue from energy sales. Finding the optimal level of transmission is therefore nontrivial.

Investors and operators could further reduce the costs of accessing remote wind power if the wind farm had the ability to store electricity during times that transmission is constrained, and sell it later when transmission is not constrained. This would allow the operator to avoid wind curtailment as well as perhaps reduce required transmission capacity even further. Using 2005 day-ahead prices in the Pennsylvania-New Jersey-Maryland Power Pool (PJM), and hourly wind output data from EWITS, Denholm and Sioshansi (2009) compared the revenue when siting CAES at a remote wind farm as opposed to siting it at load and operating it independently from the remote wind farm. At both locations, the operator is assumed to use the storage device for price arbitrage in day-ahead energy markets. When the storage capacity was co-located with the wind farm, the optimal transmission capacity would decrease since the operator could better control power delivered on the line and therefore reduce transmission capacity investment. However, this arrangement limits the operator′s ability to arbitrage prices since transmission constraints may limit the availability of the storage device compared to when it is located at load. It is this tradeoff in revenue that they used to estimate the break-even cost of transmission at which point building energy storage on-site becomes economical.

Denholm and Sioshansi (2009) results showed that for transmission costs above $450/MW-km in the Upper Midwest, energy storage (up to 30% of a wind farm′s capacity) starts to replace transmission capacity for optimal profits. While the authors used a wide range of transmission costs in their analysis, they did not vary storage costs, which are highly uncertain. It is also uncertain whether market participation would be the most economic financing arrangement for such a project, as opposed to fixed-price power purchase agreements.

In this paper we study the application of energy storage to reduce transmission capacity required to access remote wind resources. As a case-study, we focus on a wind farm in North Dakota that is built to deliver power to Illinois, and estimate the break-even capital cost of energy storage at which point it becomes an economic alternative to transmission capacity. We selected these locations because wind capacity factors are high in much of North Dakota but these farms are far away from major load centers, mainly located in Illinois.

Since transmission costs affect the viability of remote wind farms, we also find the break-even cost of transmission. To do this, we parameterize the size and costs of energy storage and transmission capacity to access the farm, and find the transmission and storage sizes that yield the lowest average cost of generating and delivering electricity ($/MW h) to end-users. This is equivalent to the annualized cost of a power plant when including transmission (Kammen and Pacca, 2004). An optimization model is developed to estimate the hourly operation of the energy storage asset given its size and the available transmission capacity. A benefit of our approach is that it provides a realistic metric for evaluating projects that could be used to set a minimum negotiated price target for a power purchase agreement. The approach also avoids making assumptions about hourly energy prices, which are highly volatile and uncertain, especially as installed wind capacity increases.

The rest of the paper is organized as follows: the next section describes the proposed project and frames the problem. Section 3 described the modeling method, Section 4 presents results, and Section 5 discusses the implications of our results.

2. Wind-storage-transmission system

2.1. Location and characteristics

We focus on the Midwest, and Illinois in particular, because of the ambitious renewable targets in this state and the general characteristics of wind power in the Midwest. Illinois has an RPS requiring 25% renewable generation by 2025, and 60–75% of this target must be met by wind power (either in or out of state). Meeting this goal would require building approximately 10 Gigawatts (GW) of new wind capacity by 2025, which would double the installed wind capacity in the entire Midwest region.[1] Illinois has good wind resources but it is also surrounded by other states that have the best onshore wind potential in the United States.[2] It is therefore an interesting area in which to study how to access remote resources since doing so might prove to be an attractive investment.

In choosing the wind site for our analysis, we relied upon wind power output data simulated by NREL for the Eastern Wind Integration and Transmission Study (Database of the Eastern Wind Interconnection Study (EWITS), 2012). For this study, NREL estimated wind energy potential for over 1300 sites across the United States. NREL first published the data in 2008 but has since updated their estimates in the summer of 2012 (Database of the Eastern Wind Interconnection Study (EWITS), 2012). At each site, NREL estimated the maximum capacity of the wind farm and simulated the resulting wind power output from 2004 to 2006 in 10-min increments. The EWITS database relies on meteorological models combined with wind turbine performance models. It thus includes a characterization of variability in wind power output that results from different meteorological conditions throughout the year. As a result, our model incorporates the effects of modeled variability in the operating decisions of the storage infrastructure.

We chose to analyze the integration of the best wind farm in the Midwest according to EWITS, which is 200 MW, has an average capacity factor of 47% in 2006, and is located in North Dakota, 1200 km from the Illinois Hub price node. Fig. 1 displays the energy system under study.

2.2. Investment decision

We study the case where a single agent builds a 200 MW wind farm in North Dakota to deliver power to Illinois. We assume that this agent must also build the infrastructure necessary to deliver the power to load (i.e., transmission and storage). Thus, the agent has to decide how much transmission and energy storage capacity to build to access the farm. We suggest that the objective of the agent is to minimize the project's average cost of generating and delivering electricity (ACE). Unlike other studies that report ACE as the cost of only generating electricity, the ACE estimates shown in the results section include *both* the costs of producing *and* delivering wind power to load. ACE is calculated by dividing the sum of annualized capital costs and variable costs for all assets by the total power delivered in one year, as shown in (1). The ACE, however, is not the objective of the optimization model that we develop. Instead, a set of scenarios with different transmission and storage size combinations are defined and evaluated using an optimization model that maximizes total delivered power for each scenario. Results from these scenarios are then used to evaluate the combinations of sizes that yield the lowest ACE under various capital cost assumptions. This will be further detailed in Section 3 of this paper.

$$\mathrm{ACE} = \frac{\text{Annualized capital cost (transmission, storage, wind)} + \text{Variable cost for 1 year(storage, wind)}}{\text{Total MW h delivered per year}} \tag{1}$$

It could be argued that the investment decision should be based on the profitability of the project, and in fact previous studies such as Denholm and Sioshansi (2009), Fertig and Apt (2011), and Mauch et al. (2012) used profit maximization in the economic analysis of storage-wind systems. We argue, however, that given the unique characteristics of the electricity markets, predicting profits using market prices is highly uncertain. We further suggest that the average cost of generating and delivering electricity (ACE) is a measure of the minimum average price the developer would need to recover costs, and could be used as a benchmark to negotiate a power purchase agreement with an electric utility. Alternatively, if the investor of this project instead participates in energy markets directly, then ACE provides a lower bound for the average market price (minus any government incentives) that the project would need to receive in order to recover costs.

2.3. Cost tradeoff between transmission and energy storage

If an energy storage technology is cost competitive, then adding storage might incentivize the decision-maker to reduce the necessary transmission investment to access remote wind power. This tradeoff, however, relies on the assumption that transmission capacity can be scaled down linearly by capacity and distance ($/MW-km). While we make this assumption, which Denholm and Sioshansi (2009), Fertig and Apt (2011), and Pattanariyankool and Lave (2010) also made, it still deserves some attention. Some costs – such as property rights, siting, and right of way – are not scalable. It's likely that these costs will be unaffected by the size of the line built since they must be incurred for any project size.

A report by American Electric Power (American Electric Power, 2006) summarized the transmission costs for a proposed line from West Virginia to New Jersey. AEP broke out the estimates of transmission costs by cost item, as summarized in Table 1. If we assume that all equipment and construction costs for the substations and lines are scalable by MW, then about 80% of the costs are scalable. We thus assume that this assumption holds true for transmission lines and that calculating transmission costs with a scalable $/MW-km metric is a reasonable approach.

[1] Required wind capacity additions in Illinois is based on 2011 generation data from U.S. Energy Information Administration (EIA) (2011) assuming 30% capacity factor and that total generation in the Midwest will decrease by 1% by 2026, consistent with projections from Annual Energy Outlook (2012). Current installed wind capacity in MISO is from Midwest Independent Service Operator (MISO) (2012).

[2] Illinois average wind capacity factors range from 32 to 44%. Neighboring states such as North Dakota, South Dakota, Iowa, Nebraska and Indiana have average capacity factors that range from 37 to 47% (Database of the Eastern Wind Interconnection Study (EWITS), 2012).

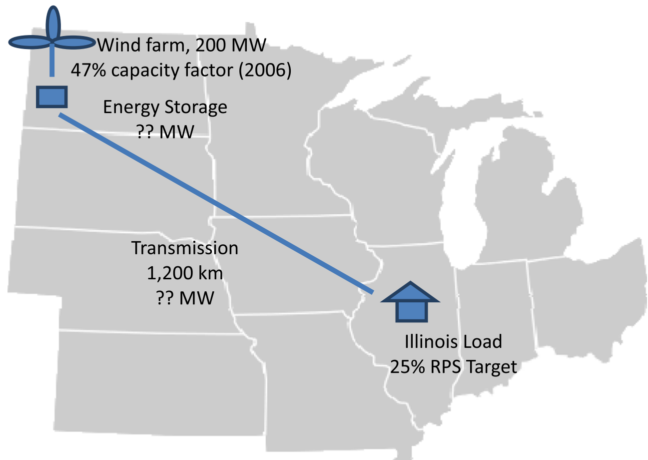

Fig. 1. Map of the Midwest region and the proposed remote wind farm in North Dakota, built to serve load in Illinois. The objective is to find the sizes (MW) of transmission and energy storage that minimize the costs of generating and delivering power.

Table 1
Cost items for the AEP interstate transmission project from West Virginia to New Jersey ($ 2006).
(*Source*: American Electric Power, 2006).

Item	Category	$ Million
Amo substation		30
Doubs substation	Equipment	154
	Property	2.5
Deans substation	Equipment	169
	Property	2.5
765 kv line	Siting	94
	Right of way	516
	Line equipment & construction	1968
Total costs		2936
Scalable costs		2321
% Scalable		79%

Scalability is also consistent with the more recent development of subscribed transmission lines. As opposed to traditional transmission projects, subscribed lines require generators to enter private contracts with the line owner to use the line. For example, for the Rocky Island Clean Line generators must negotiate contracts to use specified amounts of capacity (Rock Island Clean Line, 2012). If optimal to do so, generators could scale down their allocated transmission capacity from the contract and replace it with energy storage. We thus assume that the maximum amount of transmission that one single farm would purchase is 100% of the nameplate capacity of the farm, 200 MW in this case, and that the costs are linearly scalable by capacity and distance.

2.4. Operational decision

We assume that a single agent builds and operates the wind farm and the infrastructure necessary to deliver power to load. We use average cost of generating and delivering electricity as defined in Eq. (1) above (in $/MW h) as a metric to evaluate the size of storage and transmission to be built. We do this analysis via scenario comparison, as detailed in Section 3. If energy storage capacity is built, we assume that it will be used to maximize the total power delivered. There are considerable costs due to the variability of wind power as well as different values of electricity depending on the hour of the day (Lueken et al., 2012; Decarolis and Keith 2006). However this paper does not consider these factors. Wind power is assumed to be a "must-take" resource, no matter when it is generated or what electricity market prices are at the time. We therefore assume that the agent is only interested in maximizing the total power delivered from the farm given that capital assets are already in place.

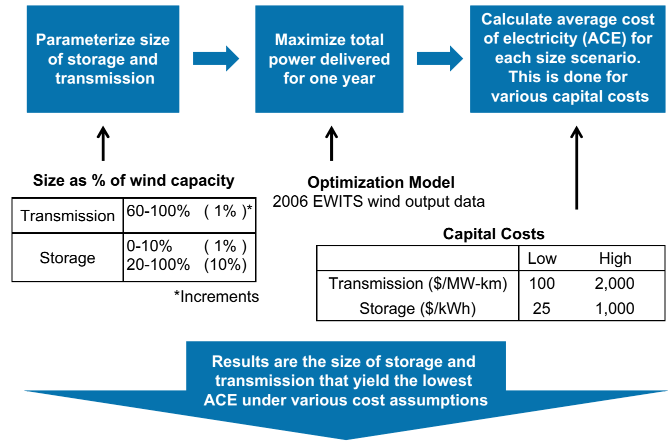

Fig. 2. Modeling approach used to find the size of transmission and storage that yield the lowest average cost of electricity (ACE, $/MW h) for the proposed project.

3. Methods and assumptions

3.1. Method overview

In order to estimate the sizes of transmission and storage that yield the lowest average cost of generating and delivering electricity, we rely on scenario analysis. We first parameterize transmission and storage sizes over wide ranges. We vary transmission size from 60% to 100% of the nameplate capacity of the farm (200 MW), in 1% increments. We vary energy storage capacity from 0% to 100% of the nameplate capacity of the farm, in 10% increments. We also vary storage at a smaller scale, 0–10% in 1% increments to see if small amounts of storage prove to be economical. Under each set of assumptions, we then use an optimization model to maximize the total delivered power from the wind-storage-transmission unit. We rely upon 2006 wind data from Database of the Eastern Wind Interconnection Study (EWITS) (2012) for the power output of the North Dakota site. We then calculate ACE ($/MW h) over one year given assumed capital costs for transmission and storage. Fig. 2 summarizes our modeling approach.

3.2. Assumptions

Due to the large uncertainty in capital costs for transmission and storage assets, we range transmission costs from $100 to $2000/MW-km and storage costs from $25 to $1000/kW h. These ranges are consistent with values reported for different storage technologies, as shown in Table 2. Note that while we use ranges of costs from the literature, we are not making any statements about the plausibility of transmission or storage reaching the low costs in our tested ranges. We also do not assess the technical feasibility of the different technologies in the region studied. We treat costs parametrically and calculate the break-even costs at which point the optimal decisions change.

Table 3 shows additional assumptions made as well as citations upon which the assumptions were based. These include a 10% discount rate to annualize capital cost as well as different lifetimes of each capital asset. We assume roundtrip efficiency for energy storage of 80% and transmission losses of 7%. We assume that the capital cost of the wind farm is $2200/kW. Annual fixed operating

Table 2
Cost estimates of energy storage technologies and transmission.

Energy storage technologies	$/kW h	Year $[a]	Source	Notes
CAES (underground)	60–125	2010$	EPRI (2010), Table 4-12	–
Sodium–sulfur	~500	2010$	EPRI (2010), Table 4-14	–
Li-ion	300–1700	2010$	Argonne National Labs (ANL) (2011), EPRI (2010), Table 4–14)	Low estimate is for 2020
Used Li-ion[b]	40–130	2012$	Neubauer and Pesaran (2012)	Estimate is for 2020
Transmission	**$/MW-km**			
	$200–900	2001$	Fertig and Apt (2011)	–
	$100–1300	Parameterized	Denholm and Sioshansi (2009)	–
	$1200–4200	2009$	Hoppock and Patiño-Echeverri (2010)	–

[a] The year in which the cost is observed is the same year as the citation unless otherwise noted.
[b] Batteries once used in electric vehicles but then repurposed for electricity grid applications.

Table 3
Cost and technology performance assumptions.

	Wind	Storage	Transmission
Lifetime (years)	20	10	40
Inv. cost ($/kW)	2200[a]	(see Table 2)	(see Table 2)
length (km)	–	–	1200
FOM ($/kW)	30[a]	2.5[b]	0
Duration (h)[c]	–	1[d]	–
VOM ($/MW h)	0[a]	7[b]	0
Efficiency		80%[b]	93%[e]

FOM=fixed operation and management costs; VOM=variable operation and management costs.
[a] Based on Annual Energy Outlook (2012) technology cost assumptions.
[b] FOM is based on costs for balance of power and power electronics for Li-ion batteries. VOM and efficiency are also based on Li-ion batteries (Kintner-Meyer et al., (2010)).
[c] Duration is the time that a storage unit can deliver its rated capacity. For example, a 100 kW battery with 1 h duration can deliver up to100 kW for 1 h, or 100 kW h total. A 100 kW battery with 2 h duration could deliver 100 kW for 2 h, but not 200 kW for 1 h.
[d] Based on Li-ion battery but also generalizable for CAES. CAES traditionally has longer duration (15–20 h) but by assuming 1 h duration, CAES will simply not have a restriction on how much it can store in any given hour. Instead, it is assumed that its limit on hourly capacity is equal to the full cavern capacity, which represents a best case scenario for this technology.
[e] Based on transmission losses of 7%, this corresponds to the average distribution and transmission losses in the U.S. according to the Energy Information Administration: (U.S. Energy Information Administration (EIA), 2012).

and maintenance costs (FOM) are assumed to be $30/kW for wind, $0 for transmission, and $2.5/kW for storage. Variable costs for wind and transmission are assumed to be $0, and $7/MW h for storage. Duration of the storage device is assumed to be 1 h. Sensitivities to these assumptions are presented in Section 4.3.

3.3. Optimization model

For each transmission and storage size, we use a linear optimization model to maximize total power delivered from the project (the denominator in Eq. (1)). As shown in Eq. (2)–(7), for each hour over one year, the model chooses when to store, transmit, or curtail power given wind output, a storage constraint, and a transmission constraint.

$$\max_{(s_{t+1},z_t)_k} \sum_{(t=0)_k}^{(T-1)_k} (q_t)_k \quad ,\forall t \in T,\ \forall k \tag{2}$$

$$s.t. \quad qt = w_t + s_t - s_{t+1} - z_t \quad ,\forall t \in T \tag{3}$$

$$0 \le s_t \le SC \quad ,\forall t \in T \tag{4}$$

$$0 \le q_t \le TC \quad ,\forall t \in T \tag{5}$$

$$(s_0)_k = (s_1)_{k-1} \quad ,\forall k \tag{6}$$

where q_t = transmitted power, s_t = power in storage, w_t = wind power produced, z_t = curtailed power, SC = storage size, TC = transmission size, t = hour, T = optimization horizon, k = model iteration, N = model horizon (7)

The model solves over a three-day (T=72) receding horizon for each hour t over one year (N=8760). Using a model predictive control technique similar to that described in Goodwin et al. (2001), the algorithm finds a solution over the optimization horizon T, saves the solution for the first hour (t=0), shifts T by 1 h, and then reruns the optimization over the new 72 h period. Iterations (k) continue until the model horizon (N) is reached.

The decision variables in the optimization are the power stored for the next hour (s_{t+1}) and the power curtailed (z_t). Ideally, the operator would not curtail any power; however, if in an hour the operator is constrained both with respect to storage and transmission (TC and SC), then curtailment is necessary. The state variables are the power available in the storage device in hour t (s_t), which is dynamically linked to the decision variable (s_{t+1}), and the wind power produced (w_t), for which we rely upon 2006 wind power output data from Database of the Eastern Wind Interconnection Study (EWITS) (2012). Hourly wind power is assumed to be known without error over the three-day horizon. Other studies that relied on wind forecasts to optimize storage, such as Mauch et al. (2012), used a shorter time horizon, 48 h, and account for the uncertainty in hourly wind power. We deliberately choose optimistic assumptions about wind power in order to design a best-case scenario for storage.

Using the model from (2)–(7), we calculate the maximum annual power delivered (q_t) by the wind farm given exogenous transmission and storage constraints (TC and SC).

4. Results

4.1. Sizing of transmission and storage

Fig. 3a and b shows the transmission and storage sizes that yield the lowest average cost of electricity (ACE) to access the 200 MW farm in North Dakota for Illinois load, while maximizing power transmitted. As transmission becomes more costly, storage capacity is used to replace transmission. However, this only occurs when storage costs are less than or equal to $100/kW h. As expected, higher storage costs become more viable (lowest ACE) as transmission costs increase. For example, at $25/kW h, storage starts to replace transmission when costs are greater or equal to $600/MW-km. At $50/kW h, storage starts to replace transmission for costs that are greater or equal to $900/MW-km. At $75/kW h, storage starts to replace transmission for costs that are greater or

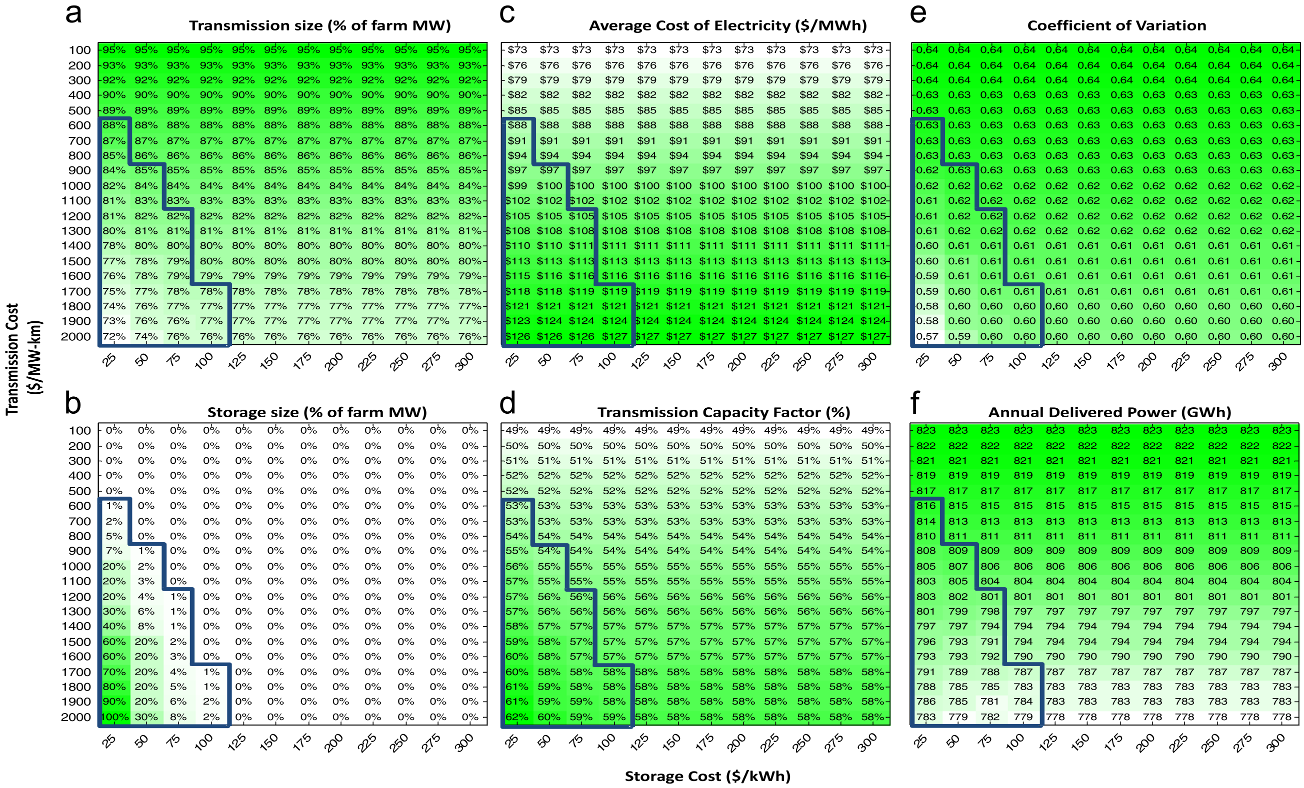

Fig. 3. (a–f): Figures show the results from finding the size of transmission and storage that provide the lowest average cost of electricity (ACE) for the North Dakota wind farm. For all figures, the *y*-axis represents the transmission costs (in $/MW-km) and the *x*-axis represents the storage costs (in $/kW h). (a) Shows the optimal size of transmission (as % of the wind farm′s capacity, 200 MW), (b) shows the optimal size of storage, (c) shows the lowest ACE ($/MW h) achieved, and (d) shows average transmission capacity factor (%). (e) Shows the coefficient of variation in hourly power delivered. (f) Shows total annual power delivered. The blue rectangles highlight the cases where storage capacity is $\geq 1\%$ of total installed wind capacity. The shading shows how values in each figure compare (green represents highest values, white represents lowest values). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

equal to $1200/MW-km. For costs of $100/kW h, storage replaces transmission for costs that are greater or equal to $1700/MW-km. Lastly, beyond $100/kW storage is uneconomical.

Fig. 3a shows that, regardless of the storage capacity available, transmission size never drops below 72% of the installed wind capacity. This demonstrates that there is a lower bound to the amount of transmission that must be built in order to deliver adequate amounts of power to make the project economical. Optimal transmission also never reaches levels higher than 95%, since the wind farm′s capacity factor is below this limit in all hours. These results are consistent with results produced by Pattanariyankool and Lave (2010), who showed that without storage, optimal transmission size is between 70% and 80% of the nameplate capacity of the wind farm.

In some extreme cases (Fig. 3b), optimal energy storage capacity can be up to 200 MW, the same size as the wind farm. For example, in cases when energy storage cost is $25/kW h and transmission costs are greater than $1000/MW-km, optimal storage ranges from 20% to 100% of wind farm capacity. These scenarios however, correspond to only optimistic cases for storage and pessimistic cases for transmission. Furthermore, the average cost of electricity for these cases (Fig. 3c) range from $99/MW h to $126/MW h, which is high relative to other technologies, including wind farms that are closer to load (Lazard, 2011). At such high costs, it is unlikely that the remote wind project would be built.

We estimate that developing a wind farm at the North Dakota site, including transmission and potential storage investments, would cost between $72/ MW h and $127/ MW h. In cases where some level of storage investment is optimal, costs are at least $88 per MW h. These estimates give a rough approximation of the average price of electricity that the project would have to receive in order to recover all costs.

Fig. 3d shows average transmission capacity factor, given different sizes of storage and transmission that yield the lowest ACE. When less transmission is added, there is a higher capacity factor on the line and with the addition of storage capacity, the capacity factor increases further as it avoids some power curtailment. The transmission capacity factors range from 49% to 62% depending on the cost scenario. Total power delivered changes less than 6% among all cases, ranging from 823 GW h to 778 GW h (Fig. 3f).

In addition to having a higher average capacity factor, the variability in power delivered also decreases with the addition of storage and the reduction of transmission capacity. Fig. 3e shows that the coefficient of variation in hourly power output ranges from 0.57 to 0.64. Fig. 4 illustrates the optimal operation of the wind-storage system when transmission capacity and storage capacity are 80% and 20% of the wind farm capacity, respectively. When wind output is higher than transmission capacity, storage is charged to avoid power curtailment and later discharged when transmission is not constrained. This results in smoother delivered power. Although we do not estimate the value of decreased variability, projects with less variability may be more valuable to system operators since they would likely require less ramping by other generators.

4.2. Trade-offs between transmission and storage

Storage does not easily replace transmission capacity economically because the marginal gains in power delivered from one more unit of storage is far lower than that gained by one unit of

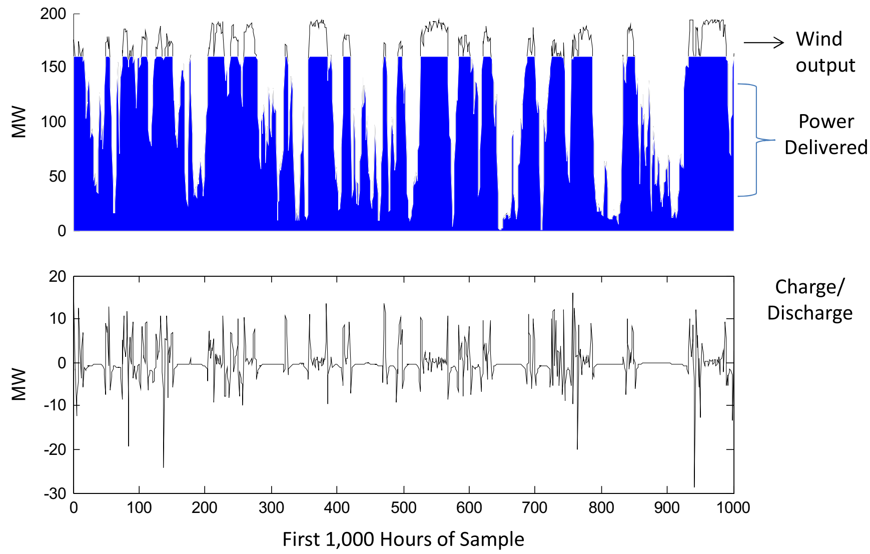

Fig. 4. The figure displays results from maximizing total power delivered from the wind-storage system with 20% storage (40 MW) and 80% transmission (160 MW). The top figure shows the wind output relative to total power delivered from the wind-storage system. When wind output is greater than transmission capacity, storage (lower figure) is charged (positive values) to avoid curtailment. Storage is then discharged (negative values) in hours when more transmission capacity is available, thereby increasing the delivered power. The result is a smoothing effect on delivered power.

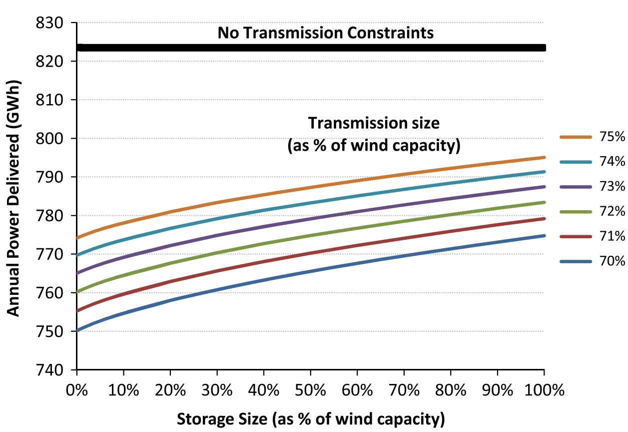

Fig. 5. Annual power delivered as the size of storage (*x*-axis) and transmission capacity (curves plotted). Not all transmission sizes are plotted. The figure highlights how one unit of transmission capacity provides much more delivered power than one unit of energy storage capacity.

transmission. This issue is illustrated in Fig. 5, which shows the marginal gain in power delivered with incremental size of storage (*x*-axis) and transmission (represented by curves). For example, when transmission size is 70% of wind capacity, increasing storage size from 0% to 100% of the farm′s capacity adds about 25 GW h of power delivered per year. Alternatively, the decision-maker could increase power delivered by the same amount by increasing transmission capacity by 5%. For the 200 MW farm considered, this corresponds to adding 200 MW of storage or only 10 MW of transmission. Despite this disadvantage however, as show in Fig. 3a, when storage is very inexpensive and transmission is expensive, optimal storage size can be up to 200 MW, the same size as the wind farm.

4.3. *Sensitivity to key assumptions*

Table 3 in Section 3.1 summarizes our assumptions of technology cost and performance characteristics for wind, energy storage, and transmission. To test the robustness of our results to these assumptions, we performed a sensitivity analysis by creating low and high cases for the most relevant assumptions (Table 4). The major factors affecting the economics of storage – other than the capital costs of storage and transmission – are storage lifetime, transmission lifetime, storage variable and fixed operating and maintenance costs (VOM and FOM), discount rate, and wind capital costs.

Table 4
Range of assumptions used in sensitivity analysis.

Sensitivities	Units	Low cost	Base cost	High cost
VOM storage	$/MW h	4	7	10
FOM storage	$/kW	1	2.5	4
Discount rate	%	20%	10%	5%
Wind capital cost	$/kW	2500	2200	1500
Lifetime Transmission	Year	30	40	50
Lifetime storage	Year	20	10	7

VOM and FOM costs for storage affect its annual operation costs and therefore how competitive storage is as a replacement for transmission. Technology lifetime determines the amount of time over which the capital costs of an asset can be discounted. Lifetime, along with the discount rate, therefore affect the average cost of electricity ($/MW h) calculation. For shorter lifetime assets like storage (10 years), we assume that the investor will reinvest in the asset after its lifetime. Because storage competes with transmission, higher transmission costs make storage more economical. Transmission lifetime is therefore inversely correlated with the break-even cost of storage. Similarly, wind capital costs are inversely correlated with storage competitiveness because the wind farm is a large fraction of the overall costs. If wind costs are very high, then adding even small amounts of storage to deliver more power will decrease the average cost of electricity (ACE), and make the project more economical. Also, because storage is a smaller portion of overall costs, higher discount rates make storage more competitive since discounting more significantly affects the economics of higher cost assets such as wind and transmission.

Fig. 6 shows the results of the sensitivity analysis. The left figure reports the maximum capital cost for energy storage that would incent some non-zero amount of storage investment

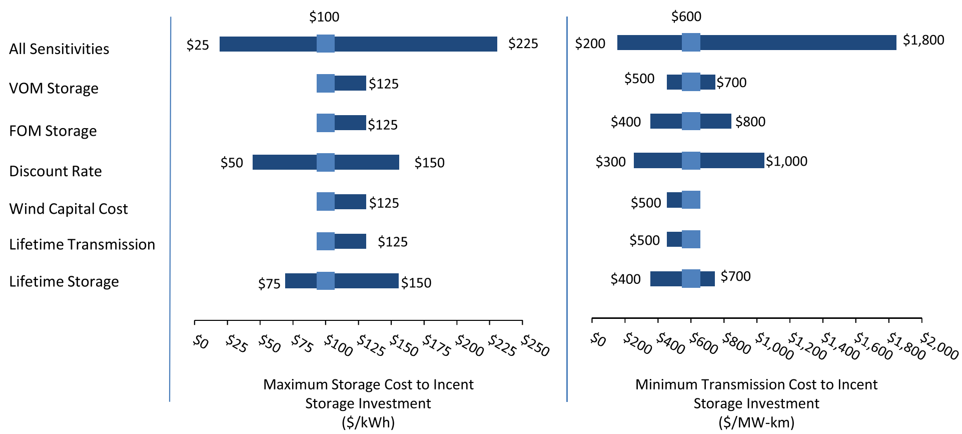

Fig. 6. Tornado diagrams showing the sensitivity of results to key input assumptions. The figures show the maximum storage cost and minimum transmission cost for storage investment to be nonzero. Blue squares represent results from the base case assumptions made in Table 3. Detailed results of the base case are available in Fig. 3(a–f). Low and high cost assumptions represent best and worst cases for storage, respectively. Because storage competes with transmission, any assumption that makes transmission more expensive allows storage to become more competitive. VOM=variable operation and management, FOM=fixed operation and management. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(break-even cost of storage). Similarly, the right figure shows the minimum transmission cost that would make the decision-maker invest in some amount of storage (break-even cost of transmission). The figure does not report the sizes of transmission and storage at these break-even costs; Fig. 3a–f reports these values for base case assumptions.

The lower bounds for VOM and FOM costs do not change the break-even cost for storage. These costs do however affect the break-even cost of transmission. The lower bounds for wind capital costs also don′t affect the results. Transmission lifetime of 50 years also doesn′t affect storage competitiveness because the difference between 40 and 50 years for discounting is trivial.

With all sensitivities included, the break-even capital cost of storage to incent storage investment ranges from $25/kW h to $225/kW h, with a best estimate of $100/kW h. Similarly, the break-even capital cost of transmission ranges from $200/MW-km to $1800/MW-km, with a best estimate of $600/MW-km.

5. Discussion

Storage might have a role in replacing transmission when integrating remote wind resources, but capital costs need to be less than $100/kW h and transmission costs need to be greater than or equal to $600/MW-km. Current storage costs are highly uncertain, but roughly 3 to 15 times higher than $100/kW h for lithium-ion batteries and 5 times higher for sodium–sulfur batteries. Of the costs shown in Table 2, only the optimistic cost estimates for CAES and used Li-ion batteries could meet this cost target. Further, our analysis of this application of energy storage assumes perfect foresight in hourly wind power for three days, which is a very optimistic assumption. It is likely that the true break-even cost of storage used as a replacement for transmission is even lower since errors in forecasting will result in suboptimal storage decisions and therefore make the storage asset less valuable.

Further, even if storage capacity was ample and free, a minimum amount of new transmission capacity must be built to deliver power. We show that the transmission capacity that is most economical ranges from 72% to 95% of the installed wind capacity across all cost scenarios. This range is consistent with previous literature (Pattanariyankool and Lave, 2010).

Although it′s unclear what transmission costs would actually be in accessing this farm, beyond a certain cost threshold, the project would not be profitable. If for example, an independent power producer could negotiate a guaranteed rate of $80/MW h (ignoring subsidies), transmission costs would need to be lower than $400/MW-km to make investing in the remote farm worthwhile. Because storage is only economic when transmission costs are beyond $600/MW-km, in this scenario, it is unlikely that storage would be used as a replacement for transmission capacity.

The addition of a production tax credit, which is currently $23/MWh, as well as renewable energy credits, which previously have been up to $20/MW h for wind generation in Illinois, might make this remote project economical even at higher capital costs. However, investors would have to manage the uncertainty in the future regulatory environment when relying on these subsidies. Our analysis provides a benchmark cost estimate with which decision-makers could use to value the profitability of such a project when considering all these factors.

The main drawback of using energy storage as proposed in this paper is that the incremental percent increase in power delivered from storage is far less than an incremental percent increase in transmission. Since we assume that the value of electricity is the same in each hour, one of the main advantages of energy storage, its ability to control when power is delivered, is eliminated. It may be that using energy storage for other applications, such as providing frequency and voltage control, would generate more value; we do not account for such effects. Similarly, using energy storage to decrease wind power variability may also provide additional value to grid operators. However, assessing this value is beyond the scope of this paper. Another possible scenario to model would be to allow the storage device to simultaneously participate in ancillary markets in the North Dakota energy markets as well as deliver power to Illinois. This optionality would increase the value of storage significantly and therefore increase its break-even value to greater than $100/kW h. Further, this analysis did not consider the use of existing transmission lines. It is possible that wind farms that are transmission-constrained by existing transmission could avoid curtailment without having to build new transmission capacity. However, given the problem framework that we′ve defined, those interested in accessing remote wind resources today are likely better off by building only transmission capacity and not energy storage. Energy storage is likely better suited for providing other services when it is not co-located with a remote wind farm.

Acknowledgements

This work was supported in part by the center for Climate and Energy Decision Making (SES-0949710), through a cooperative agreement between the National Science Foundation and Carnegie Mellon University. Additional funding was provided through the RenewElec project by the Doris Duke Charitable Foundation, the Richard King Mellon Foundation, the Electric Power Research Institute, and the Heinz Endowment. Findings and recommendations are the sole responsibility of the authors and do not necessarily represent the views of the sponsors.

The authors would also like to thank Granger Morgan, Jay Apt, Christian Blanco, Eric Hittinger, Brandon Mauch, Emily Fertig and all others who provided comments to this work.

References

American Electric Power, The AEP Interstate Project Proposal, A 765 kV Transmission Line From West Virginia to New Jersey, January 31, 2006.

Annual Energy Outlook 2012, Energy Information Administration, Table 56. Electricity Generation by Electricity Market Module Region and Source, June 2012.

Argonne National Labs (ANL), Modeling the Performance and Cost of Lithium-Ion Batteries for Electric-Drive Vehicles, Paul A. Nelson, Kevin G. Gallagher, Ira Bloom, and Dennis W. Dees, August 2011.

Daniel M., Kammen, Sergio, Pacca, 2004. Assessing the costs of electricity. Annual Review of Environment and Resources 29, 301–344.

Database of State Incentives for Renewables & Efficiency (DSIRE), Illinois Incentives/Policies for Renewables & Efficiency, March, 2013, available at: 〈http://dsireusa.org/incentives/incentive.cfm?Incentive_Code=IL04R&re=0&ee=0〉.

Database of the Eastern Wind Interconnection Study (EWITS), National Renewable Energy Lab, Update 2012, Available at: 〈http://www.nrel.gov/electricity/transmission/eastern_wind_methodology.html〉.

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

Denholm, Paul, Kulcinski, Gerald L., Holloway, Tracey, 2005. Emissions and energy efficiency assessment of baseload wind energy systems. Environ. Sci. Technol. 39, 1903–1911.

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

EPRI, Electricity Energy Storage Technology Options: A White Paper Primer on Applications, Costs, and Benefits, EPRI Project Manager D. Rastler, December 2010.

Fertig, Emily, Apt, Jay, 2011. Economics of compressed air energy storage to integrate wind power: a case study in ERCOT. Energy Policy 39, 2330–2342.

Fischlein, Miriam, Wilson, Elizabeth J., Peterson, Tarla R., Stephens, Jennie C., 2013. States of transmission: moving towards large-scale wind power. Energy Policy 56, 101–113.

Goodwin, Graham C., Graebe, Stefan F., Salgado, Mario E., 2001. Control System Design. Prentice Hall, New Jersey, pp. 724–742

Greenblatt, Jeffery B., Succar, Samir, Denkenberger, David C., Williams, Robert H., Socolow, Robert H., 2007. Baseload wind energy: modeling the competition between gas turbines and compressed air energy storage for supplemental generation. Energy Policy 35, 1474–1492.

Hoppock, David C., Patiño-Echeverri, Dalia, 2010. Cost of wind energy: comparing distant wind resources to local resources in the Midwestern United States. Environ. Sci. Technol 44, 8758–8765.

Hittinger, Eric, Whitacrel, J.F., Apt, Jay, 2010. Compensating for wind variability using co-located natural gas generation and energy storage. Energy Syst.

Jacobson, Mark Z., Delucchi, Mark A., 2011a. Providing all global energy with wind, water, and solar power, Part II: Reliability, system and transmission costs, and policies. Energy Policy 39, 1170–1190.

Jacobson, Mark Z., Delucchi, Mark A., 2011b. Providing all global energy with wind, water, and solar power, Part I: Technologies, energy resources, quantities and areas of infrastructure, and materials. Energy Policy 39, 1154–1169.

Michael Kintner-Meyer, Chunlian Jin, Patrick Balducci, Marcelo Elizondo, Xinxin Guo, Tony Nguyen, Frank Tuffner, Vilayanur Viswanathan, 2010. Energy Storage for Variable Renewable Energy Resource Integration—A Regional Assessment for the Northwest Power Pool (NWPP) IEEE.

Lazard. Levelized Cost of Energy Analysis Version 5.0., June 2011.

Lueken, Colleen, Cohen, Gilbert E., Apt, Jay, 2012. The costs of solar and wind power variability for reducing CO_2 emissions. Environ. Sci. Technol. 46, 9761–9767.

Mauch, Brandon, Carvalho, Pedro M.S., Apy, Jay, 2012. Can a wind farm with CAES survive in the day-ahead market? Energy Policy 48, 584–593.

Midwest Independent Service Operator (MISO), 2012Growth of Wind Capacity, available at: 〈https://www.midwestiso.org/WhatWeDo/StrategicInitiatives/Pages/Renewables.aspx〉.

Neubauer Jeremy Pesaran Ahmad,A techno-economic analysis of PEV battery second use: repurposed-battery selling price and commercial and industrial end-user value. In: National Renewable Energy Lab, Presented at the 2012 SAE World Congress and Exhibition, Detroit, Michigan, 2012-01-0349, April 2012.

Pattanariyankool, Sompop, Lave, Lester B., 2010. Optimizing transmission from distant wind farms. Energy Policy 38, 2806–2815.

Rock Island Clean Line, 2012, website, available at: 〈http://www.rockislandcleanline.com/site/home〉.

Trainer, Ted, 2011. A critique of Jacobson and Delucchi′s proposals for a world renewable energy supply. Energy Policy 44, 476–481.

U.S. Department of Energy (DOE), 2008. Increasing wind energy′s contribution to U.S. Electricity Supply. Energy Effic. Renewable Energy

U.S. Energy Information Administration (EIA), Electricity: Detailed data by State, 2011, available at: 〈http://www.eia.gov/electricity/data/state/〉.

U.S. Energy Information Administration (EIA), State Electricity Profiles 2010, January 2012, available at: 〈http://www.eia.gov/tools/faqs/faq.cfm?id=105&t=3〉.