Operation and sizing of energy storage for wind power plants in a market system

Magnus Korpaas\textsuperscript{a, *}, Arne T. Holen\textsuperscript{a}, Ragne Hildrum\textsuperscript{b}

\textsuperscript{a}Department of Electrical Power Engineering, Norwegian University of Science and Technology, 7491 Trondheim, Norway
\textsuperscript{b}Statkraft SF, P.O. Box 200 Lilleaker, 0216 Oslo, Norway

Abstract

This paper presents a method for the scheduling and operation of energy storage for wind power plants in electricity markets. A dynamic programming algorithm is employed to determine the optimal energy exchange with the market for a specified scheduling period, taking into account transmission constraints. During operation, the energy storage is used to smooth variations in wind power production in order to follow the scheduling plan. The method is suitable for any type of energy storage and is also useful for other intermittent energy resources than wind. An application of the method to a case study is also presented, where the impact of energy storage sizing and wind forecasting accuracy on system operation and economics are emphasized. Simulation results show that energy storage makes it possible for owners of wind power plants to take advantage of variations in the spot price, by thus increasing the value of wind power in electricity markets. With present price estimates, energy storage devices such as reversible fuel cells are likely to be a more expensive alternative than grid expansions for the siting of wind farms in weak networks. However, for areas where grid expansions lead to unwanted interference with the local environment, energy storage should be considered as a reasonable way to increase the penetration of wind power.

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Keywords: Wind power; Energy storage; Operation scheduling

1. Introduction

Wind energy is a valuable supplement to conventional energy sources, as wind power technology has become mature. However, the maximum penetration of wind power in electricity networks is limited by the intermittent nature of the energy input. Fluctuations in wind power production also make it difficult for owners of wind power plants to compete in electricity markets. Energy storage devices with the ability to store large amounts of energy for several hours or more, such as flow cells and fuel cell systems [1], could provide the necessary flexibility for smoothing of wind power. In this way, the possibilities for market operation can be improved. Moreover, for potential wind farm sites remote from a strong electrical connection point, energy storage could provide an alternative to grid reinforcements.

There is a growing research interest in using energy storage to increase the value of intermittent energy sources in electricity markets [2–4]. However, important issues such as the impact of market mechanisms, network constraints and forecasting accuracy of wind power must be further explored to fully determine the advantages and limitations of energy storage for this purpose. Therefore, a method for the scheduling and operation of such a distributed resource in a market system has been developed and implemented in a computer model. This paper aims to describe the proposed method, and to show an application of the method on a case-study, where the impact of energy storage sizing and wind forecasting accuracy on system operation and economics are emphasized.

2. System description

The distributed resource is presented in Fig. 1, and consists of a wind power plant and an energy storage device. The owner of the resource is assumed either to have a demand for electricity $P_l$ or, alternatively, to have contracts with nearby electricity consumers represented by an aggregated load demand. The system is connected to the main electricity network by a transmission line with limited capacity. Reactive power flow is neglected in the model. The system components and the electricity market model are presented below.
2.1. Wind power plant

The power output of the wind power plant is calculated from the power curve in Fig. 2. It is assumed that the wind power plant consists of identical wind turbines, and that the wind conditions are the same for all turbines.

2.2. Energy storage

The energy storage device is defined by its energy capacity, charging efficiency, discharging efficiency, charging power capacity, and discharging power capacity. The relationship between storage content $S$ and power flow in/out of the storage $P_s$ is as follows:

$$S(t+1) = \begin{cases} S(t) - \frac{1}{\eta_d} P_s(t) \Delta t & (P_s(t) \geq 0) \\ S(t) - \eta_c P_s(t) \Delta t & (P_s(t) < 0) \end{cases} $$

(1)

where $\eta_c$ and $\eta_d$ are the efficiencies of charging and discharging, respectively. The round-trip efficiency of electricity storage is $\eta_s = \eta_c \cdot \eta_d$.

2.3. External grid

The external grid will act as a power source or sink, depending on the balance between local load and generation. The power exchanged with the marked system is calculated from the power balance:

$$P_e(t) = P_w(t) + P_l(t) - P_d(t)$$

(4)

$$P_{e\text{min}} \leq P_e(t) \leq P_{e\text{max}}$$

(5)

Power export corresponds to positive values for $P_e$ and is measured at the load side of the transmission line. If the net power production exceeds the line capacity, the excess power is consumed by a dumpload $P_d$ that is used only for this purpose.

Fig. 1. Wind power plant with local energy storage connected to a scarcely populated grid. The direction of the arrows refers to positive values of the variables.

Fig. 2. The wind generator input/output characteristics.
The expression for power losses is:

\[ P_{\text{e,loss}}(t) = c_i P_e(t)^2 \]  

(6)

The maximum allowable power exchange (export) is equal to the transmission line capacity, while the minimum value (import) is given by:

\[ P_{e}\text{min} = -P_{e}\text{max} + c_i (P_{e}\text{max})^2 \]  

(7)

2.4. The electricity market

In the Nordic spot market, daily bids for sale and purchase of energy are provided to the power pool no later than 12 h before the actual day. After the spot price has been settled, the final schedule for each generator is worked out. During the operation, if a participant does not deliver the specified amount at the spot market, then the discrepancy must be settled on the regulating power market, which normally results in a reduced income [5].

Market operation is simplified considerably in the model. Since the marginal cost of power produced from a wind power plant is zero, it is presumed that wind energy always can be sold at the spot market. The bidding process is not included in the model. Each day at 12:00, the owner of the distributed resource performs the scheduling of the hourly power exchange \( P_{\text{sch}} \) for each time step in the scheduling period, which is 24 h. The hourly income from the spot market is:

\[ f_{\text{spot}}(t) = \text{SP}(t) P_{\text{sch}}(t) \]  

(8)

Power flow in the transmission line causes losses, which are bought for spot price:

\[ f_{\text{loss}}(t) = -\text{SP}(t) P_{\text{e,loss}}(t) \]  

(9)

The load income is set equal to the cost for supplying the load with electricity from the external grid, which is paid by spot price:

\[ f_{\text{load}}(t) = \text{SP}(t) (P_1(t) + c_i P_2(t)^2) \]  

(10)

This means that the owner of the wind power plant obtains an extra income due to avoided transmission costs. It is assumed that the load is deterministic.

The regulating market is simplified by using average values. The prices for sale and purchase of electricity traded on the regulating market are assumed to be proportional to the spot price:

\[ f_{\text{reg}}(t) = \begin{cases} (1 - c_{\text{ep}}) \text{SP}(t) P_{\text{dev}}(t) & (P_{\text{dev}}(t) \geq 0) \\ (1 + c_{\text{rp}}) \text{SP}(t) P_{\text{dev}}(t) & (P_{\text{dev}}(t) < 0) \end{cases} \]  

(11)

where the deviation between actual and scheduled power exchange, defined as:

\[ P_{\text{dev}} = P_e - P_{\text{sch}} \]  

(12)

is traded on the regulating market. Fig. 3 illustrates the difference between spot price and regulating price. In the Norwegian regulating market, a discrepancy between the actual and planned production could in fact lead to higher revenue, depending on the overall power balance in the market. This could for instance happen in the cases when the actual power exchange is higher than scheduled at the same time as there is a power deficit in the market. However, it is presumed that in average, deviations from the production plan are disadvantageous, since they increase the uncertainty of the overall power balance.

The annual revenue is given by the following relationship:

\[ AR = \sum_{\text{year}} (f_{\text{spot}} + f_{\text{loss}} + f_{\text{load}} + f_{\text{reg}}) \]  

(13)

3. Operation strategy

The operation strategy consists of three separate parts: (1) forecasting of wind velocity, (2) scheduling of the power exchange with the market and, (3) on-line operation of the storage. In the present model, the forecasts of load and spot price are assumed to have 100% accuracy. A flowchart of the method is shown in Fig. 4, and the various steps of the algorithm are described below.

3.1. Forecasts

A simple algorithm for computer-generated wind velocity forecasts has been developed. The forecasting is performed once each day before the operation scheduling, and is based on the prediction of mean wind velocity \( \bar{v} \) for the whole scheduling period \( t = 1 \ldots t_{\text{end}} \). It should be noticed that using this method, the forecasted wind velocity will be equal for all hours in the scheduling period. The algorithm includes the following steps:

1. Read wind data \( v(t) \) for \( t = 1 \ldots t_{\text{end}} \) and the coefficient of variation \( V \) for mean wind velocity prediction
2. Calculate \( \bar{v} \)
3. Draw a random number \( x \) from the normal distribution with mean \( \bar{v} \) and standard deviation \( \bar{v} \cdot V \)
4. Return the predicted wind velocity
\[ v(t) = x \] for
\[ t = 1 \ldots t_{\text{end}} \]

As an example, for a wind series with mean value 8.6 m/s and standard deviation of 4.4 m/s, the root-mean-squared error (RMSE) of prediction error is found to be 2.5 m/s using the proposed method with \( V = 0 \).

3.2. Operation scheduling

The operation scheduling of the system is performed at the specified hour \( t_{\text{sch}} \) each day. The objective is to find the scheduling plan for the next day which maximizes the expected profit. Since the wind velocity forecast is uncertain, and a penalty is given for trading in the regulating market, one should ideally consider the wind velocity as a random variable with a specific distribution in the optimization problem. However, at this stage of the modeling work, the forecasted values are treated as deterministic variables in order to reduce the computational effort to a reasonable size. Trading losses due to deviations between actual and scheduled generation are consequently omitted in the optimization problem.

Given the spot price, load demand and forecast of wind velocity, the optimization task is to determine the hourly trading of electricity in the spot market which maximizes the expected profit over the scheduling period. Mathematically, the scheduling problem can be formulated as:

\[
\max \left[ F = \sum_{t=1}^{t_{\text{end}}} \left( P_{\text{sch}}(t) - c_i P_{\text{ch}}(t)^2 \right) \right] \tag{14}
\]

subject to the system operating constraints (1)–(7) and the initial storage level. Since there are normally large uncertainties in the prediction of wind velocity, the optimization horizon is chosen to be only 24 h. According to Eq. (14), it is beneficial from an economic point of view to discharge the storage completely at the end of each day. However, if we have good long-term forecasts for the wind velocity, the optimization horizon should be increased. Then it could be favorable to store energy at the end of the next day, for instance if there was a risk for long periods with no wind.

The optimization problem is solved using a dynamic programming algorithm, which requires discretisation of the storage level. The optimization routine returns the optimal path for the next day \( S_i(t) \) for
\[ t = 1 \ldots t_{\text{end}} \]:

By using Eqs. (1) and (4), the scheduling of power exchange \( P_{\text{ch}}(t) \) for day \( i + 1 \) can be calculated. The dumpload \( P_d \) is only used when the storage is completely filled at the same time as the net local production exceeds the transmission line capacity. Alternatively, one or more wind turbines could be shut down or downregulated to avoid overloading the transmission line. The power losses due to downregulation of wind power output will be equal to \( P_d \).

The operation scheduling is performed 12 h in advance, which means that the storage level is unknown at the start of the optimization period. If the wind forecasts were 100% correct, the estimated value \( \hat{S}_{i(t_{\text{end}})} \) from the previous optimization should be used. However, because of uncertainties in the wind forecasts, the hourly storage levels will deviate from the estimated values. To get a new estimate of the initial storage level of day \( i + 1 \), the following equation is employed:

\[
\hat{S}_{i+1}(0) = \hat{S}(t_{\text{end}}) + \Delta S \tag{15}
\]

where \( \Delta S \) is a storage level correction based on the measured level at the scheduling hour \( t_{\text{sch}} \) and an improved forecast of the wind velocity for the remaining hours of the day.

3.3. On-line operation

A straightforward operation strategy is used. The energy storage is operated in order to follow the hourly scheduling plan for power exchange with the market. Consequently, it is presumed that the electrical energy produced by the wind storage.
power plant and consumed by the load is continuously measured.

4. System simulation

A case-study is used to test the proposed operation strategy of the distributed resource. The parameters for the base case are listed in Table 1. Time series for wind velocity are computed using a synthesis algorithm described in Ref. [6]. Time series for load demand are computed using the daily load curve in Fig. 5. The mean load for a certain day is obtained from a normal distribution \( N(\mu_l, \sigma_l) \), where \( \mu_l \) is the daily mean load and \( \sigma_l \) is standard deviation of the daily mean load. The hourly values are obtained by multiplying with the corresponding value of the curve in Fig. 5. The type of energy storage is not specified, but it could for instance be a regenerative fuel cell or a redox flow cell. It should be mentioned that such storage systems are still in the development stage, and the future specific costs are uncertain.

Electricity prices are shown in Fig. 3, and are chosen to be equal for all days. The mean spot price in the base-case is set to 30 $/MWh (270 NOK/MWh). As a comparison, the average spot price in the nordic power market in year 1996 and year 2000 were 254 NOK/MWh and 103 NOK/MWh, respectively [7] (1$ = 9 NOK in November 2001). Moreover, the variations in simulated spot price during the day are chosen to be higher than observed in the market today.

The simulated average price for purchase of electricity in the regulating market is 25% higher than the spot price, and the average price for sales is 10% lower than the spot price. These values are partly based on Ref. [5], assuming a relatively high penetration of wind power in the market.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_{e_{\text{max}}} )</td>
<td>4 MW</td>
</tr>
<tr>
<td>( P_{w_{\text{max}}} )</td>
<td>10 MW</td>
</tr>
<tr>
<td>( P_{s_{\text{max}}} )</td>
<td>6 MW</td>
</tr>
<tr>
<td>( S_{\text{max}} )</td>
<td>100 MWh</td>
</tr>
<tr>
<td>( \mu_l )</td>
<td>2.6 MW</td>
</tr>
<tr>
<td>( \sigma_l )</td>
<td>0.52 MW</td>
</tr>
<tr>
<td>( \mu_s )</td>
<td>0.75</td>
</tr>
<tr>
<td>( \sigma_s )</td>
<td>0.01 MW(^{-1})</td>
</tr>
</tbody>
</table>

Fig. 6. Actual wind power production \( P_w (\bigcirc) \) and forecasted wind power production \( \hat{P}_w (\bigcirc) \).

4.1. Demonstration of daily operation

The operation strategy will be demonstrated by presenting a 48 h simulation run of the base case. Forecasted and actual values of hourly wind power production are shown in Fig. 6.

Fig. 7 displays the scheduled and actual power exchange with the market. The system manages to follow the production plan most of the time except for some hours at the start and at the end of the simulation period. This discrepancy can be explained from Fig. 8, where the estimated and actual storage levels are plotted. At the start and the end of the period, the actual storage level is empty for a longer period than expected. For those hours, the storage cannot compensate if the wind power production is lower than predicted. This undesirable situation can be avoided by setting the minimum allowable storage level \( S_{\text{min}} \) larger than zero in the scheduling routine. Moreover, the actual power exchange also deviates from the scheduling plan for \( t = 55 \). The reason for this discrepancy is that

Fig. 5. Typical daily load curve for Norwegian households.

Fig. 7. Actual power exchange \( P_e (\bigcirc) \) and scheduled power exchange \( P_{e_{\text{sch}}} (\bigcirc) \) with the market.
the power capacity of the storage is too low compared to the wind power production in that hour.

It is important to obtain a good estimate of the initial storage level used in the optimization routine. If the actual storage level is higher than the estimate, the storage can reach its maximum value too early by following the scheduling plan. Likewise, if the storage level is lower than the estimate, the storage can be discharged too early. The latter is observed in Fig. 8, where the estimated storage level at the start of day two ($t = 49$) is higher than the actual value. This causes a full discharge of the storage at the end of the period 1 h earlier than estimated, and the system becomes less flexible.

4.2. Simulation results

A simulation study has been carried out in order to study the impact of storage design and wind forecasting error on the performance and economics of the system. The time step is 1 h, and the length of the time series is 8760 points, i.e. 1 year. The parameter values in Table 1 are used as a base case. It should be noted that the modeling method of wind speed and load described above does not take into account seasonal variations. However, the error caused by this simplification is considered to be small for Norwegian conditions, since there is a close match between the seasonal electricity demand and wind energy in several areas with good wind conditions [8].

Results from simulation runs with different storage parameters $P_s^{\text{max}}$ and $S^{\text{max}}$ are presented in Table 2. The relative deviation $P_{\text{dev}}/P_{\text{sch}}$ from scheduled power varies from 3% to 11% for the largest and smallest storage system, respectively. Thus, unpredictable variations in wind power production are smoothed by the storage most of the time. The ratio $P_d/P_w$ is a measure of the energy loss due to transmission constraints, since the dumpload is only used when the net local production exceeds the line capacity.

The relative usage of the dumpload is low for all storage designs, although there is a clear correlation with $S^{\text{max}}$. A two-fold increase in energy capacity results in a four-fold reduction in the electricity consumed by the dumpload. Moreover, an interesting effect is observed when comparing the different values of $P_d/P_w$ for $S^{\text{max}} = 50$ MWh. The usage of the dumpload actually increases slightly for increasing power capacity, although the opposite could be expected, because the ability of the storage to consume excess power also increases. However, with a higher power capacity, it is possible to store more energy during off-peak periods. Consequently, the storage will be completely filled more often. This is undesirable, but can be avoided by adding a limitation on the power capacity used in the scheduling routine.

Furthermore, Table 2 shows that the revenue increases with increasing power and energy capacity of the storage, as expected. On the other hand, the storage device is then likely to be more expensive, which is particularly true for fuel cell systems. Finding an appropriate size of the storage is not only critical for the system operation but is also of great economic importance, due to potential high investment costs. Fig. 9 displays the duration curves of charging, discharging and the energy reserve, which provides information about the utilization of the storage device. It is evident from the charging and discharging curves that an energy storage with separate charging and discharging devices (for instance an electrolyzer and a fuel cell) will have an undesirable low utilization of the total installed capacity. However, the difference between the curves implies that storage designs with different charging and discharging capacities should be investigated further. The usage of the total energy capacity is also relatively low, as can be seen from the duration curve for storage level in Fig. 9. This is beneficial from an operation point of view, since a full storage increases the risk for transmission line overload. In the case of no transmission constraints, the energy capacity could be considerably lower. Moreover, the duration curve also shows that the storage is empty for

<table>
<thead>
<tr>
<th>Storage sizing</th>
<th>$P_s^{\text{max}}$ (MW)</th>
<th>$S^{\text{max}}$ (MWh)</th>
<th>$P_{\text{dev}}/P_{\text{sch}}$ (%)</th>
<th>$P_d/P_w$ (%)</th>
<th>AR (Mill. $)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>50</td>
<td>11.2</td>
<td>4.7</td>
<td>1.059</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>100</td>
<td>10.2</td>
<td>1.2</td>
<td>1.090</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>150</td>
<td>10.1</td>
<td>0.4</td>
<td>1.096</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>50</td>
<td>7.6</td>
<td>4.8</td>
<td>1.062</td>
<td></td>
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<tr>
<td>6</td>
<td>100</td>
<td>4.9</td>
<td>1.2</td>
<td>1.097</td>
<td></td>
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<tr>
<td>6</td>
<td>150</td>
<td>4.8</td>
<td>0.4</td>
<td>1.101</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>50</td>
<td>6.6</td>
<td>4.8</td>
<td>1.064</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>100</td>
<td>3.5</td>
<td>1.2</td>
<td>1.099</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>150</td>
<td>3.2</td>
<td>0.4</td>
<td>1.104</td>
<td></td>
</tr>
</tbody>
</table>
some times. As this reduces the flexibility of the storage, one should consider to set the minimum allowable storage level in the scheduling routine higher than zero.

An essential parameter in energy storage design is the round-trip efficiency $\eta_s$. The ability to take advantage of electricity price variations is in particular dependent on the storage losses. Consequently, if the storage efficiency is low, the storage will only be used to prevent overloading of the line in cases of high wind speeds. This is illustrated in Fig. 10, where the utilization factor of $P_{\text{max}}^{\text{s}}$, defined as:

$$\text{Util. factor} = \frac{\sum_{\text{year}} |P_s(t)|}{P_{\text{max}}^{\text{s}}}$$

is plotted against the round-trip efficiency of energy storage. It is clear that the utilization factor decreases significantly for low values of $\eta_s$. Fig. 10 also shows the influence on the annual revenue. A sensitivity analysis gives that 10% improvement in the storage efficiency (from 75 to 82.5%) will lead to about 3.0% increase in the annual revenue, which corresponds to 17000 $/yr.

The economic value of accurate wind forecasts is illustrated in Table 3. As expected, the revenue is highest for perfect forecasting, since in that case all the energy can be traded in the spot market. As the forecasting error increases, it becomes more difficult to follow the scheduled production plan. Hence, more energy must be traded in the regulating market, and the revenue is reduced, according to the price curves in Fig. 3. This is particularly true when employing the persistence method of forecasting, which is simply to use the latest measured wind velocity as a forecast for the whole scheduling period. The persistence method gives a RMSE-value as high as 5.6 m/s for the wind series used here. The benefit of accurate wind forecasts depends strongly on the price difference between spot price and regulating power prices. In this study, the difference is chosen to be relatively large, which means that the effect of forecasting accuracy can be smaller in real markets.

### Table 3

<table>
<thead>
<tr>
<th>RMSE (m/s)</th>
<th>0.0</th>
<th>2.5</th>
<th>3.0</th>
<th>3.6</th>
<th>5.6</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR (Mill. $)</td>
<td>1.123</td>
<td>1.097</td>
<td>1.064</td>
<td>1.040</td>
<td>0.931</td>
</tr>
<tr>
<td>$P_{\text{dev}}/P_e$ (%)</td>
<td>0.0</td>
<td>4.9</td>
<td>12.4</td>
<td>16.9</td>
<td>38.4</td>
</tr>
</tbody>
</table>

5. Discussion

The simulation results show that with properly sized energy storage, it is possible for owners of wind power plants to take advantage of hourly price variations in the spot market. Furthermore, results obtained from the simulations should ultimately be used as a part of an economic assessment, where also investment costs are considered. It is also interesting to compare energy storage with grid reinforcements in areas where the wind power potential exceeds the capacity of the existing transmission line. The annual revenue for the base case with energy storage is 1.1 Mill.$ For comparison, simulations of the system with a new parallel transmission line instead of energy storage gives a revenue of 1.0 Mill.$.

The investment potential of energy storage as an alternative to grid reinforcements can be calculated by using the following formula:

$$I = \frac{\text{AR(wind + storage)} - \text{AR(wind + line)}}{a}$$

where $a$ is the annuity factor and AR is the annual revenue. By using Eq. (17) with a period of analysis of 20 years and 7% interest rate, energy storage would be the most economic solution if the difference in investment costs between energy storage and the new line is less than
$I = 1.06$ Mill.$.$ Present cost estimates [4] indicate that electrochemical energy storage systems are likely to be more expensive than grid reinforcements, at least in the near future. On the other hand, for areas where grid expansions lead to unwanted interference with the local environment, energy storage should be considered as a reasonable way to increase the penetration of wind power. Another alternative is to reduce the power output from the wind power plant in periods with high wind and low load by either shutting down units or downregulating the output. For the system studied here, such a strategy without the usage of energy storage would give a yearly revenue of 0.9 Mill.$.$ The energy loss due to the downregulation is 16%.

The on-line operation strategy of the energy storage described in the paper is simple, namely to follow the specified production plan. Other more sophisticated methods could be employed if wind velocity and the electricity price were represented as stochastic variables, and if forecasts were updated more frequently. The optimal power exchange with the market could for instance be updated each hour, by using principles of stochastic programming. Moreover, in some cases it will be valuable to have an energy reserve in the storage at the end of the day, for instance if high spot prices and low wind speeds are predicted for the next days. This approach is analogous to the so-called water value method used in hydropower planning [9], and will be investigated further.

It should be noticed that the proposed method is not limited to wind power, but could also be useful for the analysis of other intermittent energy resources such as solar, wave and small-scale hydro.

6. Conclusions

A method for the scheduling and operation of a wind power plant with energy storage in a market system has been presented. The method is suitable for any type of electrical energy storage and is also useful for other intermittent energy resources than wind. By implementing the method in a computer simulation model, valuable information about the impact of energy storage sizing on system operation and economics can be obtained. Simulation results of a case study show that with a properly sized energy storage, owners of wind power plants can take advantage of variations in the spot price of electricity, by thus increasing the value of wind power in electricity markets. With available technology and existing price estimates, energy storage devices such as reversible fuel cells are likely to be a more expensive alternative than grid expansions for the siting of wind farms in weak networks, although reducing the environmental impact.

Acknowledgements

This work was funded by Statkraft SF and The Research Council of Norway.

References