INCREASING THE NETWORK IN-FEED ACCURACY OF WIND TURBINES WITH ENERGY STORAGE DEVICES

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Abstract
An important operational aspect of grid-connected large-scale wind turbines is the predictability of their network in-feed. Wind power producers acting in day-ahead markets are obliged to predict their production a certain amount of hours in advance. Deviations from the predicted in-feed are alleviated by the grid operator with balancing energy at relatively high costs, depending on the market policy. Thus, the value of the annual production of a wind power producer can be significantly reduced by the penalty costs for balancing energy.

This paper investigates to what extent the accuracy of the network in-feed could be improved by combining a wind turbine with a storage device used for balancing the differences between forecasted and actual network in-feed. The relation between the storage capacity and the forecast horizon is investigated to get indications on the limitations and requirements of such a combination. A simulation algorithm is presented together with analysis methods and a case study is used to show their applicability.

Keywords: storage, wind energy, system integration, balancing markets

1 INTRODUCTION
Wind power producers acting in markets are often faced with considerable expenses for balancing energy whenever their actual production deviates from the forecasted network in-feed [1]. The major reason for these costs incurred is the difficult predictability of future wind speeds, in particular the exact timing of wind speed changes. Wind turbines need to stop at high wind speeds, exceeding defined limits, and remain turned off for a defined period because of hysteresis control. These safety shutdowns consequently result in significant power reductions in the network. Not knowing the exact timing of these shutdowns requires a considerable amount of back-up generation to be ready for a period longer than the duration of the actual in-feed outage. The back-up generators provide power for up and down regulation and their expenses are imposed as balancing penalties on the network participant for not feeding in according to his announced production schedule.

The major issue of wind power is hence the difficulty to accurately predict the variations and not the variations per se; loads always have been partly stochastic and network operators are used to deal with varying loads, using load-following power stations such as hydro and gas-fired units [1]. One possibility to compensate the differences between forecasted and actual power could be to incorporate the wind turbine in a virtual power plant scheme. The approach suggested in this study is however not to use other generators for compensating the differences but to operate an energy storage device (ESD) for balancing the deviations of the actual network in-feed from the planned network in-feed. The purpose of the storage thus is not primarily to maximize profit by feeding into the grid at financially attractive times or to save emissions, but solely to follow the production plan as accurately and reliably as possible. The production plan itself could of course be based on hourly price information, but in this study it is derived from the forecasted wind speed and the charge level of the storage device. Furthermore, the profile is kept constant over an hour, corresponding to the settlement policies of most markets.

The idea of combining a non-dispatchable generator, and in particular a wind turbine, with an ESD is not new; most publications investigating such combinations however focus on the applicability in isolated networks [2-4]. There, the purpose of the storage is to intensify the use of the wind-generated electricity, to bridge supply outages and to reduce operating hours of conventional back-up generation. Those publications focusing on grid-connected wind turbines supported by an ESD investigate either different storage operation aspects [5], balancing costs incurred [1, 6] or saved emissions when using ESDs instead of thermal units for up and down regulation [7].

Using the storage device to transform the non-dispatchable generation of the wind turbine into a deterministic network in-feed offers two advantages:

- Independent of a market structure, the wind turbine can be incorporated reliably into the day-ahead production planning, allowing dispatching former back-up generators for other purposes.
- In an electricity market, the ability to reliably determine the in-feed profile allows to accordingly sell and buy on the spot market with reduced risk of incurring balancing penalties.

The ability of the wind turbine and the storage device to effectively fulfill the predefined in-feed profile depends both on the magnitude of the forecast error and the characteristics of the ESD. The performance will be measured according to both reliability criteria as well as system losses and incurring balancing penalties. The result will be used to identify the relation between the required power and energy capacity of the ESD and the magnitude of the forecast error.
The first part of the paper presents the simulation method and procedures for the analysis of the results. The second part consists of a case study using a measured time series of 10 min wind speed values over 1 year from an on-shore measurement site in northern Norway.

2 Modeling Approach

The general model consists of three parts: the stochastic source — in this case the wind turbine —, the energy storage device and the network with the targeted in-feed profile. The targeted profile should be fulfilled as exactly as possible and can also be considered as the load, which the wind turbine has to supply together with the ESD. However, compared with isolated systems, surplus energy (i.e. energy that exceeds both the capacity of the storage and the projected in-feed) is not wasted but can be fed into the network. Still, every kilowatt-hour injected as surplus yields less income than when injected as part of a schedule. As surplus energy can be principally avoided by installing a larger storage capacity, a trade-off establishes between storage capacity and surplus energy, sold for less than its actually possible value. This aspect will be discussed in more detail later in the case study, section 4.

As mentioned, the simulation method is intended to be used with time series, which can both be measured or simulated series of an arbitrary step size. The algorithm's flow chart is depicted in Figure 1 and follows the approach used in [8]. The algorithm begins with the initialization phase, after which the simulation loop starts. At the beginning of each loop cycle, it is checked whether a new forecast period starts \((t = t_{fc})\). If so, the new forecast is calculated, depending on parameters set in the initialization phase. Based on the forecast and information on the actual charge level of the ESD, the new in-feed profile is then calculated. Afterwards, the loop continues, operating the storage device based on the actual wind turbine output, in order to meet the planned in-feed profile as exactly as possible. The cycle ends by progressing one step in the time series and by updating the charge level of the ESD, according to the actual storage action. If the time series reaches the end \(t = T\), the loop and the algorithm terminate. The following sections will discuss the main elements of the algorithm in more detail.

2.1 Initialization

During the initialization phase, both the wind speed series as well as the forecast error function \(f_{fc}\) (see below) are loaded and the simulation parameters are set. These parameters are the forecast horizon and the storage device’s energy capacity \(E_{st}\), power rating \(P_{st}\), charge efficiency \(\eta_{ch}\) and discharge efficiency \(\eta_{dch}\). Furthermore, the wind turbine's power rating \(P_{wt}\), cut-in wind speed \(v_{cin}\), cut-out wind speed \(v_{cout}\), cut-back-in wind speed \(v_{bin}\) and the cut-back-in hysteresis window duration \(t_{cb}\). Wind turbines need a minimum wind speed for operating \((v_{cin})\) and have to stop if the wind speed exceeds their cut-out velocity \((v_{cout})\). In order to prevent a wind turbine from turning on and off in fluctuating gusts, a hysteresis control is used: if the wind speed exceeds \(v_{cout}\), the rotor stops and waits for the wind speed to stay below the cut-back-in wind speed \(v_{bin}\) for at least \(t_{cb}\).

The storage device is assumed to be non-ideal and thus a portion of the originally generated electricity is used for conversions, when charging and discharging the ESD. However, most of the generated electrical energy is fed directly into the network, without being stored at all, as the ESD is mainly used for balancing the deviations from the planned hourly mean. This behavior is illustrated in Figure 2 and has to be taken into account when planning the network in-feed. For this reason, a so-called usage factor \(\beta_{usg}\) is defined, relating the forecasted generation of the wind turbine \(P_{fc}\) with the generation \(P_{planned}\) planned to be injected [8]:

\[
\sum_{t=1}^{T} P_{planned}(t) = \beta_{usg} \cdot \sum_{t=1}^{T} P_{fc}(t) \tag{1}
\]

The usage factor satisfies \(0 \leq \beta_{usg} \leq 1\) and should not be mistaken for the overall storage efficiency \(\eta_{ch}, \eta_{dch}\). If both the forecasted wind speed would be perfect and the ESD would be lossless, \(\beta_{usg}\) could be set to 1. The more the ESD is used, continuously charging and discharging, the further the factor \(\beta_{usg}\) should be reduced to take the increasing conversion losses into account. A \(\beta_{usg}\) near 1 will result in a comparatively high targeted in-feed profile, which might be difficult to fulfill. A lower in-feed profile in turn, following a lower \(\beta_{usg}\), will be better achievable, but – depending on \(E_{st}\) – result in a comparatively larger amount of surplus energy to be sold for less than its actually possible value. The factor \(\beta_{usg}\) can either be constant for the whole simulation or it can be dynamic, according to the actual charge level of the ESD. The benefit of using a dynamic \(\beta_{usg}(t)\) to incorpor-

### Figure 1. Flowchart of the simulation algorithm.

### Figure 2. Illustration of the power flows and the associated efficiencies.
rate the momentary charge level into the in-feed profile planning procedure will be discussed later on.

### 2.2 Forecast calculation

In day-ahead markets, bidding usually ends at noon and contains the bids for the following day. Thus, the production is forecasted between 12 and 36 hours in advance, based on a wind speed prediction [1]. Using the actual characteristics of the wind turbine, the wind speed forecast is then translated into a power output forecast. Various forecasting techniques exist, and their performance is usually measured as the root mean square error (RMSE) between the forecasted power output $P_{fc}$ and the actual measured power output $P_{ut}$, relative to the wind turbine's rated power $P_{rt}$ [9].

$$ f_{RMSE} = \frac{1}{P_{rt}} \sqrt{\sum_{t=1}^{T} [P_{ut}(t) - P_{fc}(t)]^2} $$  \hspace{1cm} (2)

Thus, forecasting techniques are used for predicting future wind speeds, but the actual performance of the forecast is measured at the output of the turbine. This makes sense, in particular because of the earlier discussed cut-in and cut-out behavior of wind turbines: wrongly predicted wind speed changes, exceeding the cut-out velocity $v_{cut}$ will result in significant differences between forecasted and actual power output. Figure 3 shows the consequences of a differently forecasted wind speed change. The predicted wind speed rises later than the actual wind speed, consequently exceeding the cut-out wind speed $v_{cut}$ later, suggesting a longer power in-feed than actually occurs (shaded area).

![Figure 3. Forecasted and actual wind speed and the associated power output.](Image)

It is however not the focus of this study to evaluate different forecasting techniques. There is rather a method required, which allows for choosing the forecast error at the beginning of a simulation. This is necessary for investigating the relation between forecast error and required energy capacity of the ESD.

As the simulation is based on a time series, the actual wind speed measurement $V_n$ for the next forecasting period $n$ is known. It can thus be used and superimposed with a certain error, resulting in the required forecast error $f_{RMSE}$. One method suggests using the measurement $V_n$ and adding a normal distribution in every hour [10]; this method however merely generates a swing around the actual measurement, does not show the typical forecast deviations and partially ignores dependencies from hour to hour. A different approach was suggested in [8], using an exponentially weighted sum. The measurement of the actual day is weighted and superimposed with the weighted measurement of the previous day.

$$ V_{fc,n}(\alpha) = \alpha \cdot V_n + (1 - \alpha) \cdot V_{n-1} $$  \hspace{1cm} (3)

Thus, the measurements of the previous day and the actual day are combined in order to simulate a forecast with a certain error. Hence, this approach can also be understood as a combination of persistence (using the measurement of the previous day as the forecast for the next day) and meteorological predictions (using the measurement for the actual day and reducing it by a weight). The weighting factor satisfies $0 < \alpha < 1$, whereas $\alpha = 1$ corresponds to a perfect forecast. For forecast errors $f_{RMSE} > 0$, a look-up table containing the corresponding $\alpha$ can be created. This can be achieved by calculating the forecast series with various values of $\alpha$. Using the power curve of the wind turbine, the forecasted and the actual series are then each translated into a power output and their RMSE is calculated from Eq. (2). The look-up table is then created by simply assigning each calculated $f_{RMSE}$ to its corresponding $\alpha$.

One aspect when dealing with wind speed forecasts is the time dependence of the forecast error: the error increases with an increasing forecast horizon. Forecasting methods have improved significantly over the last few years [9], but forecast errors still show a certain time dependence. A recent study from Risø National Laboratory [11] contains a comparison of different forecasting methods with different actual measurements and the resulting average error evolvement can be identified to satisfy

$$ f_{RMSE}(t_h) = 0.07 + (t_h - 1) \cdot \frac{0.03}{47} $$  \hspace{1cm} (4)

In contrast to the otherwise used time step $t$, $t_h$ represents hourly values. As mentioned, in day-ahead markets forecasts for the next day are calculated by noon. According to Eq. (4), the forecast error for the first hour of the new period hence corresponds to $f_{RMSE}$ = 0.07766, as the hour from midnight to 1 o’clock corresponds to the 13th hour after noon. For the simulation algorithm, this means that the forecast can be calculated at the beginning of the new forecast period, however using the error that corresponds to the 13th hour. As the error evolves with the duration of the forecast period, for every hour of the forecasted period a different error and hence a different $\alpha$ has to be used. The vector $V_{fc,n}$, containing the values of the new forecast period, has to be constructed from segments of forecasts with different errors in order to result in a forecast with a realistically increasing forecast error.

$$ \begin{bmatrix} V_{fc,n,0} \cdot (\alpha_{forecast}(13)) \\ V_{fc,n,1} \cdot (\alpha_{forecast}(14)) \\ \ldots \\ V_{fc,n,23} \cdot (\alpha_{forecast}(36)) \end{bmatrix} $$  \hspace{1cm} (5)
2.3 Definition of in-feed profile

As already mentioned, the in-feed profile is kept constant for the duration of an hour. It is determined at the same time as the wind speed forecast, right at the beginning of the new forecast period, as long as the according forecast error is taken into account. The in-feed profile can then simply be found as the hourly averages of the forecasted power output, adjusted with the usage factor $\beta_{\text{usg}}$, in correspondence to Eq. (1).

2.4 Storage operation

The purpose of the storage device is to both balance the deviations between the actual wind turbine output and the planned hourly power level as well as to compensate the differences between the forecasted and the actual hourly mean; the better the forecast, the more the storage is only used for smoothing the output. For this simulation, no particular storage control has been used. Defining the in-feed plan as the hourly mean value of the forecasted power output, results in having a quite even distribution of the deviations between the actual curve and the hourly smoothed curve (Figure 4). This indicates rather balanced charge and discharge requirements in order to meet the planned output.

![Figure 4. Distribution of the differences between the turbine's forecasted output curve and the hourly in-feed plan.](image)

Following the approach outlined in [8], assuming that the ESD can switch immediately between charging and discharging, allows defining the power demand $P_{\text{st, dem}}$, required from the ESD for every time step $t$ as

$$P_{\text{st, dem}} = P_{\text{planned}} - P_{\text{st}} \quad (6)$$

A negative $P_{\text{st, dem}}$ stands for charging periods and vice-versa. The ESD can only fulfill the demanded action if both the required power does not exceed the power limits of the ESD and if the momentary charge level allows withdrawing or storing the desired amount of energy. The effective power flow from or into the storage thus is

$$P_{\text{st, eff}} = \begin{cases} P_{\text{st}} , & |P_{\text{st, dem}}| > P_{\text{st}} \\ P_{\text{st, dem}}, & |P_{\text{st, dem}}| \leq P_{\text{st}} \end{cases}, \quad (7)$$

Accordingly it must then be checked whether the momentary charge level $E_{\text{st, ch}}$ allows performing the desired action. For the charge case, i.e. when $P_{\text{st, dem}}$ is negative,

$$P_{\text{st, eff}} = \begin{cases} P_{\text{st, eff}}, & E_{\text{st, ch}} - P_{\text{st, eff}} \cdot \Delta t \cdot \eta_{\text{ch}} \leq E_{\text{st}} \\ -(E_{\text{st}} - E_{\text{st, ch}}) \cdot \Delta t^{-1} \cdot \eta_{\text{ch}}^{-1}, & \text{else} \end{cases} \quad (8)$$

The variable $\Delta t$ represents the frequency of a time step related to an hour (e.g. $\Delta t = 1/6$ for 10 min values). With $E_{\text{st, min}}$ representing the minimum charge level of the ESD, the equivalent relation for the discharge state is

$$P_{\text{st, eff}} = \begin{cases} P_{\text{st, eff}}, & E_{\text{st, ch}} - P_{\text{st, eff}} \cdot \Delta t \cdot \eta_{\text{deh}}^{-1} \geq E_{\text{st, min}} \\ (E_{\text{st, ch}} - E_{\text{st, min}}) \cdot \Delta t^{-1} \cdot \eta_{\text{deh}}^{-1}, & \text{else} \end{cases} \quad (9)$$

For smaller energy capacities $E_{\text{st}}$, the effective action of the storage $P_{\text{st, eff}}$ will possibly often be smaller than the demanded power $P_{\text{st, dem}}$, as the remaining capacity is not sufficient to fulfill the requirements. Particularly, when a prediction assumes the cut-out wind speed to be reached later, the ESD must bridge a power outage of a 2 MW turbine during e.g. 10 min, which requires a considerable amount of stored energy.

3 ANALYSIS PROCEDURE

So far, a simulation method, including a forecast simulation approach, has been presented and discussed. This section contains procedures for the analysis of the simulation results and they will be applied later in the case study in order to evaluate the relation between storage capacity and magnitude of the forecast error. As the purpose of the ESD is to compensate consequences of the forecast error, the performance can be measured by investigating how reliably a certain combination of turbine and ESD can actually fulfill the planned in-feed profile and for what price (i.e. system losses and amount of surplus energy).

The vector $P_{\text{infeed}}$ contains the actual in-feed and deviates from the planned in-feed $P_{\text{planned}}$ whenever the ESD could not perform as wished. The so-called fulfillment factor $F$ will be used to quantify the accuracy of fulfilling the planned profile [8]. It basically relates the amount of insufficient energy $E_{\text{insuff}}$ to the totally planned in-feed energy $\sum P_{\text{planned}}$. According to Eq. (10), $E_{\text{insuff}}$ corresponds to the total energy of all time steps, where the in-feed was less than planned. When regarding the in-feed profile as a load to be fulfilled, $E_{\text{insuff}}$ equals the known index ‘energy not supplied’ [12].

$$E_{\text{insuff}} = \Delta t \cdot \sum_{t=1}^{T} \max(0, P_{\text{planned}}(t) - P_{\text{infeed}}(t)) \quad (10)$$

$$F = 1 - \frac{E_{\text{insuff}}}{\Delta t} \cdot \left( \sum_{t=1}^{T} P_{\text{planned}}(t) \right)^{-1} \quad (11)$$

The energy $E_{\text{conv}}$ used for conversion when charging and discharging the storage device can be calculated with the effective storage action $P_{\text{st, eff}}$ over the whole time series according to Eq. (12). The first sum considers all cases where $P_{\text{st, eff}}$ is negative, i.e. the ESD is being charged, and the second sum considers the discharge events.

$$E_{\text{conv}} = \Delta t \cdot \left[ \sum_{t=1}^{T} \max(0, -P_{\text{st, eff}}(t) \cdot (1 - \eta_{\text{ch}})) + \sum_{t=1}^{T} \max(0, P_{\text{st, eff}}(t) \cdot (\eta_{\text{deh}}^{-1} - 1)) \right] \quad (12)$$
The third measure is surplus energy $E_{\text{plus}}$, defined as the total amount of injected energy exceeding the planned in-feed profile.

$$E_{\text{plus}} = \Delta t \sum_{t=1}^{T} \max(0, P_{\text{infeed}}(t) - P_{\text{planned}}(t)) \quad (13)$$

The quantity $E_{\text{plus}}$ can be considered as the complement of $E_{\text{insuff}}$ and if both of them were zero, the planned profile would have been fulfilled exactly. The fulfillment factor $F$ indicates how reliably the projected profile was fulfilled, whereas $E_{\text{plus}}$ indicates how much energy had to be sold below price. Both measures can thus be used for analyzing the already partly discussed trade-off between surplus energy, larger storage capacity and usage factor $\beta_{\text{usg}}$. The following case study will both show the applicability of the simulation algorithm and discuss the relations between these three mentioned parameters.

4 CASE STUDY

The subject of the case study is a measurement series, consisting of 10 min wind speed measurements over the duration of a year, from a measurement site located in northern Norway. The characteristics of the wind turbine and the storage device are summarized in the following tables. The power output of the wind turbine is calculated from the power curve of the turbine, defined by the listed characteristics. The rating of the wind turbine is 2 MW.

### Table 1. Characteristics of the wind turbine.

<table>
<thead>
<tr>
<th>cut-in wind speed</th>
<th>cut-out wind speed</th>
<th>cut-back-in wind speed</th>
<th>hysteresis window</th>
</tr>
</thead>
<tbody>
<tr>
<td>$v_{\text{min}}$</td>
<td>$v_{\text{max}}$</td>
<td>$v_{\text{kip}}$</td>
<td>$t_{\text{hyst}}$</td>
</tr>
<tr>
<td>4 m/s</td>
<td>25 m/s</td>
<td>22 m/s</td>
<td>10 min</td>
</tr>
</tbody>
</table>

### Table 2. Characteristics of the storage device.

<table>
<thead>
<tr>
<th>charge efficiency</th>
<th>discharge efficiency</th>
<th>minimal energy content</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\eta_{\text{ch}}$</td>
<td>$\eta_{\text{dch}}$</td>
<td>$E_{\text{st,min}}$</td>
</tr>
<tr>
<td>0.9</td>
<td>0.9</td>
<td>0 kWh</td>
</tr>
</tbody>
</table>

The energy capacity $E_{\text{st}}$ is not defined in Table 2 as it is one of the parameters to be varied. The power rating $P_{\text{st}}$ of the ESD could be set equal to that of the wind turbine if both devices are connected to the same interface. Otherwise, Figure 4 indicates that most of the required power flow into and out of the storage is below 500 kW. This quantity will be subject of the first analysis, discussed in the next paragraph. The remaining parameters to be defined are the usage factor $\beta_{\text{usg}}$ and the forecast error $f_{\text{MAPE}}(t)$: a reference value for the usage factor is set as $\beta_{\text{usg}} = 0.98$, but will be derived later-on with an optimization, and the forecast error follows the relation defined in Eq. (4).

To investigate the influence of the power rating $P_{\text{st}}$ and the energy capacity $E_{\text{st}}$ of the storage, both values were varied from 100 to 2'000 kW, respectively kWh and the resulting fulfillment factor was calculated. The result, displayed in Figure 5, shows the stronger dependence from the energy capacity for reaching the planned profile. It additionally shows the earlier raised assumption (see Figure 4) that the influence of power ratings above 600 kW is negligible. For the remainder of the study, the ESD’s power rating is thus set at $P_{\text{st}} = 600$ kW.

The above figure also shows that a usage factor of $\beta_{\text{usg}} = 0.98$ results in a high in-feed profile level, as it can only be fulfilled in nearly 98% of all times. The small gradient of the surface indicates that a significantly larger energy capacity would be necessary for further increasing the fulfillment factor. A suitable usage factor can also be found through an optimization prior to the simulation. Different optimality criteria can be defined, choosing among the indices introduced in section 3. For the case study, both the optimal constant $\beta_{\text{usg}}$ and the optimal dynamic $\beta_{\text{usg}}(t)$ are defined to minimize the absolute difference between surplus and insufficient energy $|E_{\text{insuff}} - E_{\text{plus}}|$. The chosen optimality criterion assumes balancing energy for up- and down-regulation to be equally penalized. If up-regulation, i.e. capacity for compensating insufficient in-feed power, is more costly than down-regulation, the optimization target can be adjusted accordingly.

With the optimal factor found, it is possible to incorporate the momentary charge level of the ESD into the planning of the next day in-feed profile. If the storage device is fully charged at the beginning of a new period, the in-feed will be planned slightly higher than if the storage device were empty. Figure 6 shows the fulfillment factor for increasing energy capacities, illustrating the influence of implementing a dynamic $\beta_{\text{usg}}(t)$ instead of a constant $\beta_{\text{usg}}$. It can be seen that a dynamic usage factor only has an influence for larger storage capacities.

Figure 7 shows the associated values of surplus and insufficient energy as well as of the conversion losses, both when applying a dynamic and a constant usage factor. The conversion losses increase when using a dynamic usage factor, as the storage is used more intensively. On the other hand, the deviations from the planned in-feed decrease significantly. Altogether it can be stated that the dynamic usage factor only seems to be useful when the ESD’s capacity is large enough to offer certain flexibility.
This conclusion is confirmed by Figure 8, showing the duration curves of the storage device. Periods at the top left and bottom right corners, where the values reach the limits 1 and 0, indicate moments where the ESD was fully charged or empty, respectively. Intuitively, a well dimensioned ESD would hardly be in these areas. With the smaller capacity $E_{st} = 1'000$ kWh, the storage is empty for more than a month, independent of the usage factor. In addition, during almost 2 months, the storage is too small as it reaches its charge limit. With the larger capacity $E_{st} = 10'000$ kWh on the other hand, the improved utilization of the storage because of a dynamic usage factor $\beta_{usg}(t)$ can be identified from the figure.

![Figure 8. Storage duration curve for optimal dynamic $\beta_{usg}(t)$ and optimal constant $\beta_{usg}$.](image)

Table 3. Minimal required $E_{st}$ to achieve a fulfillment of $F > 0.98$ for different forecast horizons, dynamic $\beta_{usg}(t)$.

<table>
<thead>
<tr>
<th>$E_{st}$</th>
<th>6 hours</th>
<th>12 hours</th>
<th>24 hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>[MWh]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$I_{MSE}$ range</td>
<td>2.26</td>
<td>7.33</td>
<td></td>
</tr>
<tr>
<td>$E_{insuff}$ [MWh]</td>
<td>12.3 (2.0%)</td>
<td>111.9 (1.9%)</td>
<td>111.5 (2.0%)</td>
</tr>
<tr>
<td>$E_{plus}$ [MWh]</td>
<td>91.5 (1.6%)</td>
<td>99.0 (1.7%)</td>
<td>105.2 (1.8%)</td>
</tr>
<tr>
<td>$E_{conc}$ [MWh]</td>
<td>98.4 (1.7%)</td>
<td>107.1 (1.9%)</td>
<td>122.5 (2.1%)</td>
</tr>
</tbody>
</table>

Even though the forecast error magnitude changes little from hour to hour, the required energy capacity increases almost linearly. Surplus energy increases as well, despite the larger storage; the reason for this behavior is the limited power rating $P_{st}$, not allowing the storage to absorb to full production of the turbine. Without an energy storage device, the fulfillment factor is $F = 0.8934$, the corresponding insufficient energy is $E_{insuff} = 616$ MWh and the surplus energy equals $E_{plus} = 536$ MWh. Installing a storage device thus results in roughly additional 800 MWh, which can be sold as planned and which do not result in balancing penalties. Consequently, installing a storage device improves the value of the wind turbine, as its produced energy can be used more appropriate.

5 CONCLUSION

This study presented a time-series based simulation for using storage devices to compensate forecast deficits of the network in-feed of a wind turbine. The case study showed the applicability of the presented algorithm and analysis methods. Longer forecast horizons need significantly larger storage capacities to fulfill the planned profile in 98% of all times. Without storage device, roughly 15% of the generated electrical energy would result in balancing penalties. Because of the storage, this share can be reduced to about 4%, resulting in roughly 800 MWh, which can be sold as planned. However, larger storage capacities can only be used beneficially if their charge level is incorporated into the in-feed planning process.

6 ACKNOWLEDGMENT

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7 REFERENCES