IET Generation, Transmission & Distribution

Research Article

A new strategy based on hybrid battery–wind power system for wind power dispatching

ISSN 1751-8687
Received on 20th March 2017
Revised 2nd July 2017
Accepted on 8th August 2017
E-First on 12th October 2017
doi: 10.1049/iet-gtd.2017.0454
www.ietdl.org

Mehrdad Gholami[1], *Seyed Hamid Fathi*[1] ✉, *Jafar Milimonfared*[1], *Zhe Chen*[2], *Fujin Deng*[2]
[1]*Electrical Engineering Department, Amirkabir University of Technology, 424 Hafez Ave, Tehran, Iran*
[2]*Energy Department, Aalborg University, Aalborg, Denmark*
✉ *E-mail: fathi@aut.ac.ir*

Abstract: Battery energy storage system (BESS) is one of the best solutions to compensate the wind power fluctuations and forecasting errors for participation in the power markets by contribution in the energy production several hours ahead. Based on coordination of BESS and wind power, this study aims to present a new strategy to optimise the BESS size and increase the battery lifetime. In the proposed strategy, the average wind power is considered as the dispatch power to minimise the battery capacity and two back up battery sets are utilised to avoid shallow charge–discharge cycles for saving the battery efficiency and lifetime. In addition, the short-term operation criterion is chosen to deal with the prediction error effects. The proposed method is applied to a 2 MW wind turbine as a case study with 2 years wind data. Simulation results show the effectiveness of the proposed strategy.

Nomenclature

P_w	instantaneous wind power
P_b	instantaneous battery power
P_d	dispatching power
$P_{b(r)}$	required battery power capacity
$P_{max(i)}$	maximum battery power over each subinterval
E_b	instantaneous battery energy
$E_{b(r)}$	required battery energy capacity
SOC	state of charge of battery
$P^1_{b(r)}$	required battery power capacity in the first method
$P^2_{b(r)}$	required battery power capacity in the second method
$P^p_{b(r)}$	required battery power capacity in the proposed method
$E^1_{b(r)}$	required battery energy capacity in the first method
$E^2_{b(r)}$	required battery energy capacity in the second method
$E^p_{b(r)}$	required battery energy capacity in the proposed method
T^1_b	battery lifetime in the first method
T^2_b	battery lifetime in the second method
T^p_b	battery lifetime in the proposed method
V_f	forecasted wind speed
V^u_f	upper limit of forecasted wind speed
V^l_f	lower limit of forecasted wind speed
μ	normalised mean value of prediction error
σ	normalised standard deviation of prediction error
l	confidence level
V_r	rated wind speed
V_w	instantaneous wind speed (in p.u.)
P^u_f	upper limit of forecasted wind power
P^l_f	lower limit of forecasted wind power
P^{avg}_w	average wind power over dispatch intervals

1 Introduction

Renewable energy sources, in particular the wind turbines, are going to be a significant part of power systems [1, 2]. Owing to its fluctuations, high penetration of wind power may affect the quality and stability of power systems [3, 4]. The traditional approach to compensate the wind power fluctuations is the use of spinning reserve in the grid. High level of wind power, however, increases the overall cost of reserve units. In addition, in the modern power markets the generating units are required to commit the power production in a day or several hours ahead. Any deviation from the scheduled dispatch power results in penalties [5, 6]. Despite of intermittency and uncertainty of wind speed, it is required to generate some stable and smooth power for a given time interval, based on the predicted wind speed.

Although there are many prediction methods, which can foresee the wind profile with acceptable precision [7, 8], error in the predicted wind power is inevitable [9, 10] and prediction of the exact power is impossible. In addition, there are some extent of wind power fluctuation during the dispatching interval (e.g. one hour), despite of spatial smoothing in wind farms [11]. Therefore, injecting the specified constant power during dispatching intervals requires compensation of the prediction error and the wind power fluctuation.

Battery energy storage system (BESS) is acknowledged as one of the best solutions to remedy the wind power fluctuations and wind power prediction errors [12–18]. A number of studies have investigated hybrid wind-battery systems. Using two battery sets, as the complement of wind turbine, has been presented by Yao *et al.* [19], in which, during a given time interval one battery is charged, while the other is discharged, injecting a constant power into the grid. In this scheme, batteries with high power and energy capacities, in the range of the wind farm, are required. In some recently proposed methods, the battery is used as a subsidiary element beside the wind system that needs smaller battery capacity [20–26]. Since the application of the battery is to compensate the difference between dispatched power and the wind power, hence, the strategy for determining the dispatched power during time intervals affects the battery size and lifetime. There are two general strategies; using the mean value and using the min–max values of the predicted wind power as the dispatched power during time intervals [20–26]. The first strategy, which uses the mean value [20–22], has two advantages. It needs low power and energy capacity of the battery, and, regarding the wind forecasting, prediction methods usually have better performance with the mean value rather than the instantaneous values. Besides, there are several error distributions for estimation of the average wind power [7, 8, 10]. However, because of fluctuations around the mean value, the battery compensates the short time negative and positive deviations. This causes many shallow charge–discharge cycles,

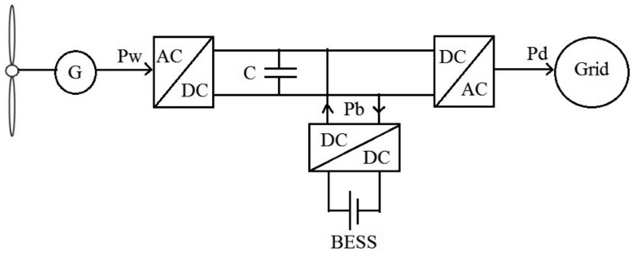

Fig. 1 *Schematic of hybrid wind-single battery system*

leading to reduction of the battery lifetime [23, 24]. On the other hand, the second approach uses the min–max values of wind power as the dispatched power, depending on the charge or discharge mode of the battery [23, 25, 26]. This strategy has the advantage of longer battery lifetime, due to avoiding shallow charge–discharge cycles. However, in turn, the battery compensates the difference between minimum and maximum wind power at each interval, so it requires a larger power capacity than the first method (average method). In addition, this method needs to forecast the instantaneous values of the wind power to find the minimum and maximum values. Beside their advantages and disadvantages, in both approaches the overall battery cost is relatively high.

The above mentioned references consider only the wind power profile to determine the power dispatch, i.e. according to wind power forecasting and of course the battery situation, the amount of power dispatch is announced. However, there are some studies which also consider the energy price profile. In these studies, at high energy price times the hybrid battery-wind system tries to sell more energy by discharging the batteries, whereas, at low energy price times it tries to dispatch less power by charging the batteries [27, 28]. Despite the advantages of this method, it requires large battery capacity in the range of wind farm, which is not economic with regard to the high costs of battery systems.

As the BESS should compensate the prediction error, so the amount of this error affects the battery sizing. There are some papers which concentrate on the forecasting methods in order to decrease the wind power prediction error, and subsequently, optimise the battery sizing by using predictive control methods [29, 30].

In this paper, a new strategy based on BESS and wind systems is presented to optimise the battery power and energy capacity and increase its lifetime. In the proposed strategy, the mean value of wind power is used as the dispatched power to reduce the battery capacity, and two battery sets are used to avoid shallow charge–discharge cycles for increasing the battery lifetime. In addition, the short-term operation, considering the effect of prediction error on the required battery capacity is investigated.

This paper is organised as follows. In Section 2, the wind–battery system is described to determine the battery size. The proposed strategy is presented in Section 3. The short-term operation is analysed to consider the prediction error in Section 4. Then a case study is performed in Section 5. Finally, a conclusion is presented in Section 6.

2 Wind–battery systems

Power market requires the generation levels several hours in advance for specific time intervals, e.g. 1 hour, which is known as dispatched power (P_d) [31]. Since the wind power has fluctuations within the time range of <1 h, even in the range of minutes [11], thus it is not constant for dispatching interval. In addition, the prediction error results in the deviation of dispatched power from the real power. Therefore, the hybrid wind-BESS strategy is used to compensate the power fluctuation and prediction error. The schematic of a hybrid wind–battery system, with single battery, is shown in Fig. 1.

The variable speed wind turbine with full rated converter is considered and the BESS is connected to the DC link via a DC/DC converter.

In this system, the battery compensates the difference between wind power (P_w) and dispatched power (P_d). Hence, the battery exchanged power (P_b) at each instant is

$$P_b = P_w - P_d \quad (1)$$

Implementation of hybrid wind-BESS includes two stages; determining the strategy to select the dispatched power for time intervals and the required battery characteristics. In this section, first by considering the specified dispatched power, the required battery characteristics are discussed and then different strategies to select the dispatched power are analysed.

2.1 Determining the required BESS

The characteristics of the required BESS are determined according to the long-term wind data and dispatched power as described below. It is assumed that the dispatched power is known as discussed in Section 2.2.

2.1.1 Power capacity: The power capacity of the battery is the nominal energy exchange rate of the battery, which must be determined using (1) for the given period T of wind power (P_w) profile. First, the period T is divided into N subintervals of 1 h dispatching time. Then for each subinterval the maximum battery power ($P_{\max(i)}$) is calculated, and finally the largest value of the local maxima is considered as the required battery power ($P_{b(r)}$)

$$P_{b(r)} = \max_T \{P_{\max(i)}, \quad i = 1:N\} \quad (2)$$

2.1.2 Energy capacity: It is defined as the total energy that a battery can deliver/absorb during complete charge/discharge cycles. Energy capacity depends on the power capacity and is obtained by integrating the battery power over time. The maximum value over the period T (a long time period, e.g. 2 years) is considered as the required battery energy capacity ($E_{b(r)}$), as presented in (3), in which $P_b(\tau)$ is the instantaneous battery power

$$E_{b(r)} = \max_T \left\{ E_b(t) = \int_0^t P_b(\tau)\,d\tau \right\} \quad (3)$$

2.1.3 State-of-charge (SOC): SOC indicates the amount of residual energy level in the battery at each time. The SOC can be obtained according to the following equation:

$$\mathrm{SOC}(t) = \mathrm{SOC}(t_0) + \frac{\int_{t_0}^t P_b(\tau)\,d\tau}{E_{b(r)}} \quad (4)$$

SOC level should be managed in a safe range ($\mathrm{SOC}_L \leq \mathrm{SOC} \leq \mathrm{SOC}_H$). The maximum level is limited to the rated energy level, i.e. fully charged (SOC = 1) and the minimum level is limited to the maximum allowable discharge without damaging the battery [32]. In addition, there is another parameter known as depth of discharge (DOD) which indicates the amount of discharge in each cycle. Because of random fluctuations in wind power, the battery may experience deep and shallow discharges.

2.1.4 Lifetime: Usually the battery lifetime is defined based on the rated number of complete charge–discharge cycles (N_r) under rated power and energy condition. If the time of each cycle, according to the rated energy and power capacity, is defined as T_c, the total time T_t, which is used as the battery lifetime in this paper, can be obtained as

$$T_t = N_r * T_c \quad (5)$$

The values of N_r and T_c and consequently T_t are considered for ideal condition (rated power capacity and complete cycles), so in non-ideal condition they would be changed. For example, in

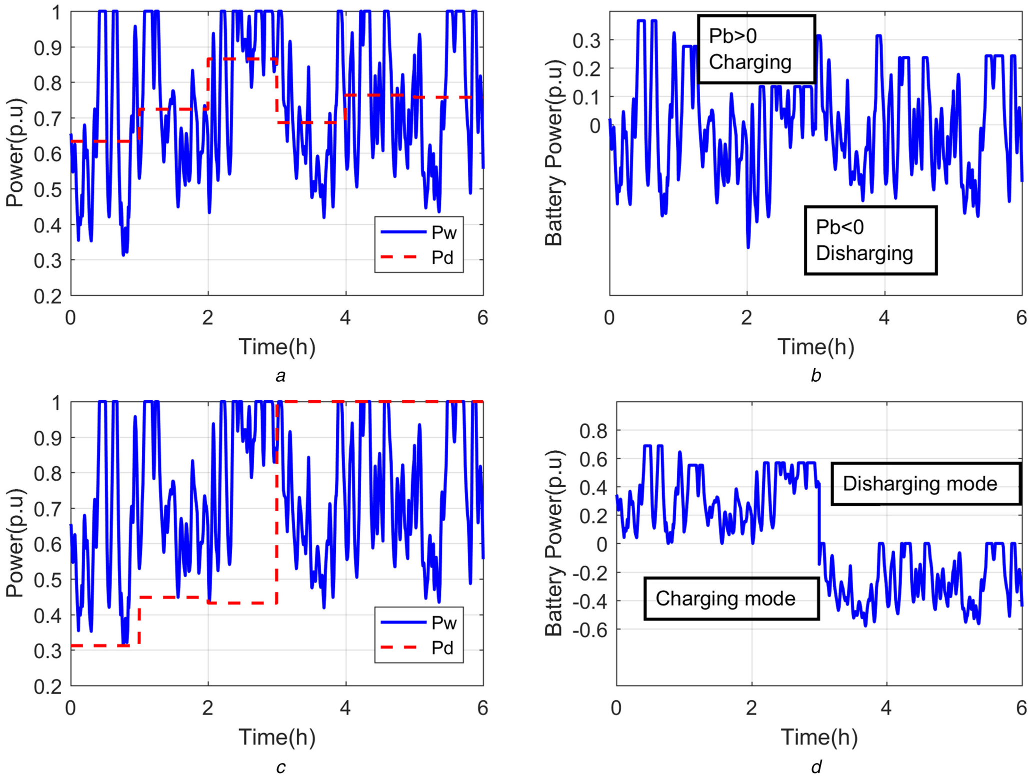

Fig. 2 *Dispatched and battery power*
(a) Wind power and dispatched power, *(b)* Battery power, in mean value method, *(c)* Wind power and dispatched power, *(d)* Battery power, in min–max value method

shallow cycles (short cycle time), despite the number of cycles is increased but the throughput and the total time (lifetime) is decreased [33]. In wind applications, there may be shallow and deep discharges, therefore, the number of charge–discharge cycles, consequently, the lifetime of the battery can be affected by DOD level [33]. Deep (complete) discharge cycles are suggested to be used in solar and wind applications to achieve longer lifetime [23, 24].

2.2 Power dispatching strategy

In addition to the wind power fluctuations, the amount of dispatched power affects the battery capacity (1). The dispatched power is the amount of power that has to be submitted to the power market several hours ahead. Usually it is defined as scheduled power for the next dispatching interval T_d (usually $T_d = 1$ h) [17]. There are two general approaches to determine the dispatched power according to the wind power [21–31]. In this section, the prediction error is neglected, but it will be discussed in Section 4.

2.2.1 Mean value: In this strategy, mean value of the estimated wind power is considered as the dispatched power (P_d) for each dispatching interval (T_d). For a typical wind power profile, the dispatched power and battery power, in a 1 h dispatching time ($T_d = 1$ h) schedule, obtained by the mean value strategy are shown in Figs. 2*a* and *b*. In this method, depending on the sign of battery power, the battery mode (charging or discharging) is changed fast from one mode to the other, so the battery experiences many shallow charge–discharge cycles (Fig. 2*b*).

2.2.2 Min–max value: In this strategy, complete charge–discharge cycles are defined for the battery and shallow charging–discharging is avoided. So according to the battery mode, i.e. charging or discharging, the minimum or maximum value of the wind power is considered as the dispatched power, respectively. The dispatched power and battery power for a typical wind power are shown in Figs. 2*c* and *d*, respectively.

As it is seen in Figs. 2*b* and *d*, depending on the dispatching strategy, the required battery power and the number of charge–discharge cycles in each interval are different. The mean value strategy needs less power capacity but the battery experiences many shallow charge and discharge cycles with uneven DOD levels (Fig. 2*b*). Against, in the min–max method, the battery experiences complete charge–discharge cycles, which improves the battery lifetime. Of course it needs larger power capacity, approximately two times that of the former method, which is the deficiency of this method for the high cost of battery (Fig. 2*d*). Therefore, the first method has the advantage of requiring battery with lower capacity, but the second method is better from the point of complete charge cycles, which results in longer lifetime [33]. In addition, regarding power prediction, the first method needs only to forecast the mean value of wind power for each dispatching interval, while the second method needs the instantaneous values of wind power to find the maximum and minimum power. Prediction methods are usually defined to predict mean value of the wind data, and also the prediction error analysis and error distribution are performed for mean value [8, 10]. So using the mean value for dispatching power is more feasible than the min-max values. By the way, there are some methods which predict wind speed over subintervals <1 h [34], which uses an artificial neural network method over 10 min intervals. In the next section the proposed method is presented to overcome the disadvantages of these methods.

3 Proposed method

Concerning battery costs, the desirable condition is having low capacity and using the battery in complete charge/discharge cycles to prevent deficiency in the battery lifetime. The mentioned strategies, each has just one of these points. In this paper, a new strategy is proposed which has both advantages together. This method uses mean value for the dispatched power, similar to the first method, so it needs less power capacity for the battery. On the other hand, two battery sets are proposed to be used, where in each interval one of them is only charged and the other one is only discharged. Hence, the battery sets do not experience many shallow charge–discharge cycles like in the first method. For a typical wind power shown in Fig. 2*a*, the charging and discharging power of the two batteries are shown in Fig. 3*a* (the dispatched power in the proposed method is same as in Fig. 2*a*, which is the mean value of wind power).

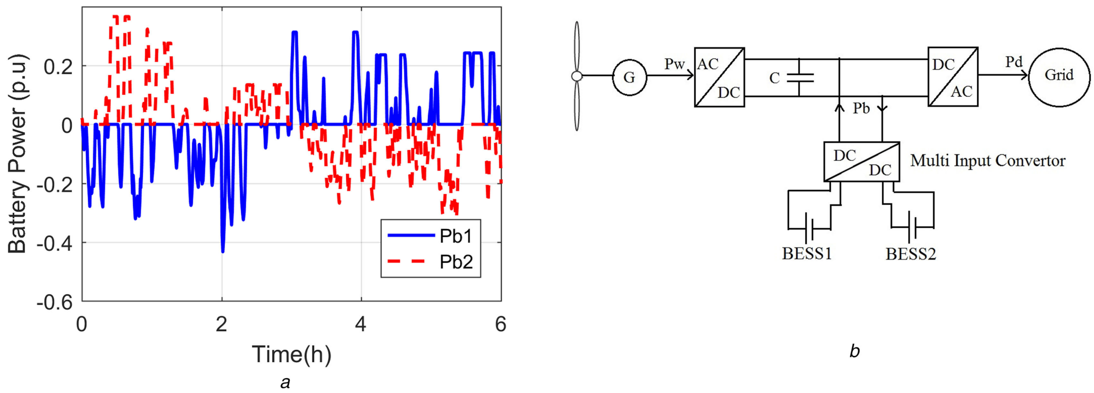

Fig. 3 *Proposed wind-battery system with two battery sets*
(a) Battery power in the proposed method, ***(b)*** Schematic of the proposed hybrid wind–battery system

As it is seen, the power profiles in Figs. 2*b* and 3*a* are the same, but in the first method (Fig. 2*b*), the power fluctuation is handled by one battery, while in the proposed method it is handled by two batteries. In the first method, the battery mode changes according to the sign of the battery power (negative or positive), while in the proposed method the negative powers within an interval are responded consistently by one battery and the positive powers by the other one, and the battery roles are interchanged during subsequent intervals. So in the proposed method both batteries experience complete charge–discharge cycles. The schematic of the proposed strategy is shown in Fig. 3*b*. Since the proposed method uses average wind power, so it needs low power and subsequently low energy capacity. In addition, full charge–discharge cycles are performed, so it insures good efficiency in terms of battery lifetime.

In the proposed approach, two batteries with the same capacity are connected to the dc link via a multi-port converter. It should be noticed that the two batteries should have the same capacity to reach their max/min SOC at the same time. In other words, at the time of role interchange, both batteries should be charged/discharged completely, otherwise, the battery with larger capacity is not completely charged/discharged and not fully utilised.

Compared with the other approaches, the following points can be deduced for the proposed method.

3.1 Power capacity

Since in both the first method and proposed method, the dispatched power is same and equal to the mean value, so according to (1) and (2), the required power capacity is the same for these two strategies. On the other hand, in min-max method, the required power capacity in each interval is the difference between minimum and maximum values of the wind power, which is larger than the difference between maximum (or minimum) and mean values, used in the proposed and first methods (Figs. 2*b*, *d* and 3*a*). So the required battery power capacity in the three methods ($P^1_{b(r)}, P^p_{b(r)}, P^2_{b(r)}$) can be compared as:

$$P^1_{b(r)} = P^p_{b(r)} < P^2_{b(r)} \tag{6}$$

In this paper, indices 1, 2 and p are used for the first (average) method, second (min–max) method and the proposed method, respectively.

3.2 Energy capacity

Since in the first method charge and discharge time intervals are not even and depend on the wind speed fluctuations, the battery mode is changed quickly and the required energy capacity is determined by (3), for the time subintervals corresponding to the powers above and below the mean value. Whereas, the second and proposed methods consider the complete cycles, so that, the long term data is divided into several intervals (m intervals) with equal durations (ΔT) as charge–discharge cycles (ΔT is different from T_d and might be considered several times larger than it). Then the maximum value of energy during these intervals is considered as the required energy capacity. So the required energy capacity for the proposed and second methods can be described alternatively by (7), which is somewhat different from (3).

$$E_{b(r)} = \max_{T} \left\{ E_{bi}(t) = \int_{\Delta Ti} P_b(\tau)\,d\tau, \quad i = 1:m \right\} \tag{7}$$

In which, $E_{b(r)}$ is the total energy for both battery sets in the proposed method, i.e. the sum of $|P_{b1}|$ and $|P_{b2}|$.

Unlike the first method, in the proposed method and second method, the required energy not only depends on the wind power, but also depends on the time duration (ΔT) of each cycle, so that larger ΔT leads to larger energy capacity. Now the required energy capacity for these methods is compared as fallows. It is obvious that the first method needs less energy capacity, because the charge–discharge cycles are shorter than in the other methods. In the first method, the charge–discharge time duration is always less than the dispatching interval (T_d). Since the battery power has zero mean value in each dispatching interval, it has at least one charge and one discharge period during each dispatching interval. Whereas for the two other methods the charge–discharge cycle may take several dispatching intervals. Then it can be deduced that the first method needs less energy capacity compared to the other methods

$$E^1_{b(r)} < E^p_{b(r)} \text{ and } E^2_{b(r)} \tag{8}$$

To compare the second method with the proposed method, the same charge–discharge cycle time ($T_c = \Delta T$) is assumed for both methods. In the proposed method, the sum of energy capacities for both battery sets at each interval (ΔT) can be written as below:

$$E^p_b = \int_{\Delta T} |P_b(t)|\,dt = \int_{\Delta T} |P_w(t) - P_w^{avg}|\,dt \tag{9}$$

In which P_w^{avg} is the average wind power over each interval. For the second method (assuming the battery is in discharging mode, so the maximum power P_w^{max} is selected as the dispatched power), the energy value in discharge interval can be written as

$$E^2_b = \int_{\Delta T} (P_w^{max} - P_w(t))\,dt \tag{10}$$

The wind power in each interval can be considered as the sum of average value (P_w^{avg}) and fluctuating part ($p(t)$).

$$P_w(t) = P_w^{avg} + p(t) \tag{11}$$

By substituting (11) into (10), the energy capacity for discharge interval can be obtained as

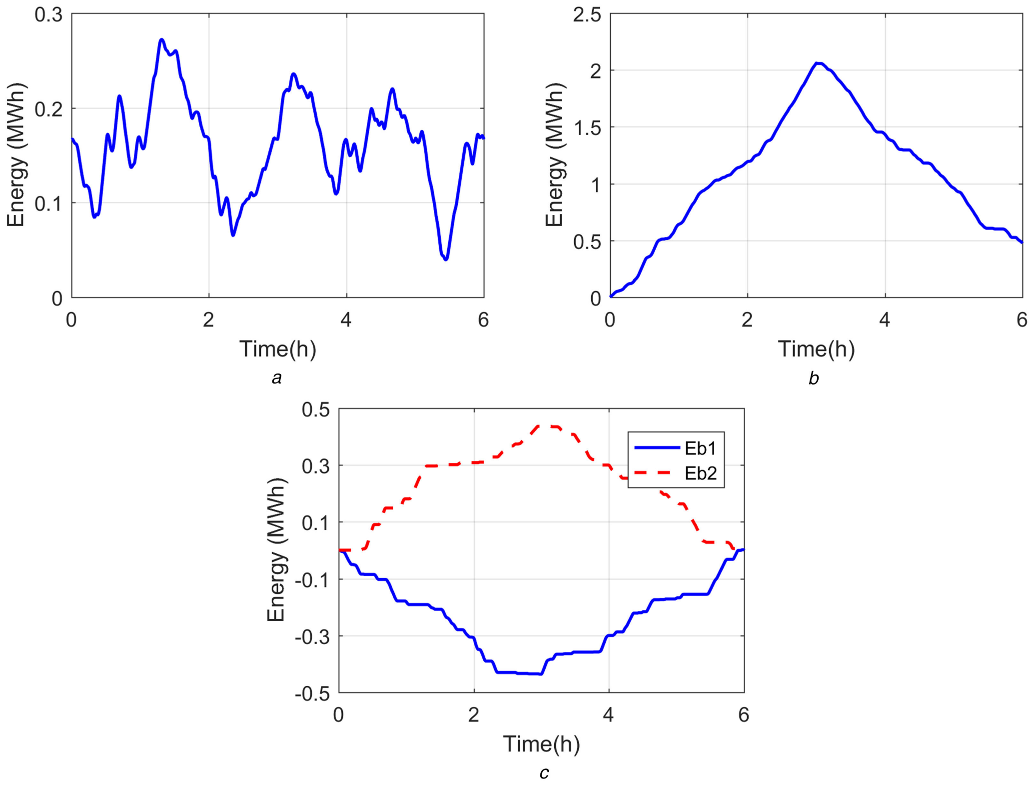

Fig. 4 *Required energy capacity in three methods*
(a) First method, ***(b)*** Second method, ***(c)*** Proposed method

Table 1 Comparison between three methods from point of battery characteristics

	Power capacity	Energy capacity	Lifetime
proposed method	low	medium	good
second method	high	high	good
first method	low	low	weak

$$E_b^2 = \int_{\Delta T} (P_w^{max} - (P_w^{avg} + p(t)))\,dt = (P_w^{max} - P_w^{avg})\Delta T \quad (12)$$

Since always $P_w(t) \le P_w^{max}$, so according to (9) and (12)

$$\int_{\Delta T} |P_w(t) - P_w^{avg}| dt \le (P_w^{max} - P_w^{avg})\Delta T \\ \xrightarrow{\text{yields}} E_{b(r)}^p < E_{b(r)}^2 \quad (13)$$

Similar result can be obtained for charge mode by using P_w^{min} as the dispatched power in (10). Equation (13) shows that the proposed method always needs lower energy capacity than the second method. Therefore, according to (8) and (13), it can be deduced that

$$E_{b(r)}^1 < E_{b(r)}^p < E_{b(r)}^2 \quad (14)$$

For the typical wind power profiles, presented in Figs. 2*a*, *c* and 3, the required energies are shown in Fig. 4 for the three methods. As it is seen the first method needs the least capacity (0.3 MWh in this example), but with many shallow charge–discharge cycles. The proposed method requires 0.9 MWh for both battery sets, and the second method needs the largest capacity, 2 MWh. A 6 h cycle time (T_c) has been assumed for the second and proposed methods.

3.3 Lifetime

Since the first method has many uneven charge–discharge cycles (Fig. 6*a*), so the battery lifetime in this method cannot be estimated analytically. However, because of many shallow cycles and fast mode changing, this method has shorter lifetime [23, 24]. On the other hand, the other two methods experience complete charge–discharge cycles so they have better performance from the point of lifetime.

It should be noticed in these two methods, there is a trade-off between energy capacity level and life time. For example, in Section 3.2, a 6 h cycle time was assumed and according to this time the energy levels were computed. Different energy capacity would be obtained if another cycle time was considered. As it was deduced, for the same cycle time, the proposed method needs less energy capacity (14). In other words, if the same energy capacity is considered for both methods, the cycle time in the second method should be smaller than the proposed method. Therefore, considering the same number of cycles, it can be deduced that in the case of equal energy capacity, the proposed method has longer lifetime

$$T_b^1 < T_b^2 < T_b^p \quad (15)$$

According to the above sections, a comparison between the three methods is shown in Table 1. As it is seen, the proposed method has better performance in terms of power, energy capacity and lifetime.

4 Short-term operation

The wind farm operators have to submit the production level to the power market several hours ahead. They are not allowed to change the announced power a few hours before the appointed time, otherwise, they are penalised for any deviation from the set points [6]. So because of uncertainty, the wind power has to be forecasted in order to estimate the dispatched power several hours in advance.

Fortunately there are several methods that can predict wind speed, and in turn wind power according to the speed–power curves, with suitable precision. However, the error in wind perdition is unavoidable, so this error has to be considered in determination of dispatched power for the next intervals. In fact, BESS has to compensate not only the power fluctuation but also the forecasting error. The wind speed prediction error is dependent on the time horizon of forecasting. Usually for time scales less than one day it has a normal distribution [10, 35]. Of course because of nonlinear speed–power curve, the wind power prediction error cannot be stated in a normal distribution [10]. In this section, at first the dispatched power, considering the prediction error, is investigated and then the battery operation for short term is discussed.

4.1 Dispatched power

Forecasted wind speed values have usually some deviation from the real wind speed. The authors of [10, 35] have shown that the wind speed prediction error (the mean speed over 1 h) has normal distribution around the forecasted speed. A normal distribution with mean value μ and standard deviation σ can be described around the forecasted value ($V_{\rm f}$) between an upper ($V_{\rm f}^{\rm u}$) and lower ($V_{\rm f}^{\rm l}$) limits as below [23, 25]:

$$\begin{aligned} V_{\rm f}^{\rm u} &= V_{\rm f} + (\mu + l\sigma)V_{\rm r} \\ V_{\rm f}^{\rm l} &= V_{\rm f} - (\mu + l\sigma)V_{\rm r} \end{aligned} \tag{16}$$

In which $V_{\rm r}$ is the rated wind speed and l indicates the confidence level. As an example, $l = 2$ results in 97% confidence level [36]. The mean and standard deviation values are normalised by the rated speed and they depend on the terrain type and time of the day, and are obtained according to the forecasting implementation over a long time real data [10].

Then wind power forecasting can be determined according to the speed–power relationship of the wind turbine (for wind farm, one has to consider wake effect and spatial smoothing to obtain wind power). The speed–power relationship for a wind turbine in per unit is given in the following equation:

$$P_{\rm w} = \begin{cases} 0, & V_{\rm w} \le V_{\rm cut-in} \\ V_{\rm w}^3, & V_{\rm cut-in} < V_{\rm w} \le V_{\rm r} \\ 1, & V_{\rm r} \le V_{\rm w} < V_{\rm cut-out} \\ 0, & V_{\rm w} \ge V_{\rm cut-out} \end{cases} \tag{17}$$

Below cut-in and above cut-out speeds, the wind system is stalled. For speeds between cut-in and rated values, the wind power is a cubic function of the wind speed, and from the rated speed up to the cut-out speed the power is limited to its rated value ($P_{\rm w} = 1\,{\rm p.u.}$). So according to (17), the forecasted wind power can be obtained for each predicted wind speed. However, depending on the wind speed range, the wind power prediction error has different significances, as for above rated speed, power is limited to the rated value and prediction error has no significance. On the other hand, for below rated speed if the upper limit of the forecasted speed is lower than the rated speed ($V_{\rm f}^{\rm u} \le V_{\rm r}$), then the wind power has a normal distribution similar to that of wind speed, but with larger standard deviation because of cubic function. Conditions might be different for speeds close to the rated, cut-in and cut-out values. In overall, according to (16) and (17) the following relationships can be defined for upper and lower ranges of wind power forecasting, considering the prediction error

$$\begin{aligned} P_{\rm f}^{\rm l} &= \begin{cases} 0, & V_{\rm f}^{\rm l} \le V_{\rm cut-in} \\ (V_{\rm f}^{\rm l})^3, & V_{\rm cut-in} \le V_{\rm f}^{\rm l} \le V_{\rm r} \\ 1, & V_{\rm r} \le V_{\rm f}^{\rm l} \le V_{\rm cut-out} \\ 0, & V_{\rm f}^{\rm l} \ge V_{\rm cut-out} \end{cases} \\ P_{\rm f}^{\rm u} &= \begin{cases} 0, & V_{\rm f}^{\rm u} \le V_{\rm cut-in} \\ (V_{\rm f}^{\rm u})^3, & V_{\rm cut-in} \le V_{\rm f}^{\rm u} \le V_{\rm r} \\ 1, & V_{\rm r} \le V_{\rm f}^{\rm u} \le V_{\rm cut-out} \\ 0, & V_{\rm f}^{\rm u} \ge V_{\rm cut-out} \end{cases} \end{aligned} \tag{18}$$

In which, $P_{\rm f}^{\rm l}$, $P_{\rm f}^{\rm u}$ are lower and upper limits for forecasted wind power, respectively. Therefore, according to (18) and (16) the forecasted wind power can be obtained as $P_{\rm f}^{\rm l} \le P_{\rm f} \le P_{\rm f}^{\rm u}$. As stated, the forecasted wind power is used to determine the dispatched power, which has some deviation from the available wind power. In fact, BESS has to compensate not only the power fluctuation but also the forecasting error. Since the difference between available power and forecasted value has to be compensated by BESS, to have a balance between charge and discharge cycles, the upper and lower forecasted values are selected as the dispatched power alternatively. This concept is shown in Fig. 5*a*. As it is seen, for the first interval the upper forecasted value is considered as the dispatched power and for the next interval the lower forecasted value.

As the prediction error should be compensated by BESS, so the amount of this error directly affects the required battery capacity. Therefore, the precision of forecasting method can optimise the battery capacity. There are many studies on prediction methods in order to optimise the battery capacity [29, 30]. In this study, an artificial neural network method [34] has been used for prediction.

4.2 Battery operation

The dispatched power is determined according to the forecasted wind power, so in this condition the dispatched value is not necessarily equal to the mean value of the real power. Also as indicated in Figs. 2*a* and 3, the dispatched value and battery power are different. For a typical wind power, the dispatched power, battery power and energy level in the proposed method, considering the prediction error are shown in Figs. 5*b*–*d*. Comparison of results in Figs. 2*a* and 5*b* shows that the dispatched powers are different because of considering prediction error. For some intervals the dispatched value is less than the real mean value and for some other intervals it is more than the real mean value. The battery power and energy level are also shown in Figs. 5*c* and *d*. The power and energy level are larger than those without considering prediction error (Figs. 2*b* and 4*c*).

In addition, from Fig. 5*d*, there is an inequality in energy levels of the battery sets. For example, when the battery 1 reaches the complete level at time $t = 3$ h, battery 2 has got just 70% of its complete level. This problem is due to the inequality in power profiles (Fig. 5*c*) of the two batteries, which is resulted by prediction error. Whereas in the case of without prediction error the battery power profiles are the same (Fig. 3*a*). In other words, in Fig. 3*a*, the dispatched power is the mean value of wind power profile, so the integration of battery powers on each half-cycle for both batteries are the same and they reach to full-charged/discharged point at the same time. However, in Fig. 5*c*, the dispatched power is not the mean value of the wind power profile, so there is an inequality in the integral of battery powers. Since the dispatched power is selected between the upper and lower forecasted powers consecutively, if the same number of repetitions of upper and lower forecasted powers in each charge/discharge half-cycle is selected, then the effects of negative and positive errors can be cancelled and the integral of batteries power would be balanced. This means that the half-cycle time should be selected an even multiple of dispatched time; $\Delta T/2 = (2n) * T_{\rm d}, n = 1, 2, \ldots,$ as shown in Fig. 6. As it is seen, by selecting $(\Delta T/2) = 4 * T_{\rm d} = 4\,{\rm h}$,

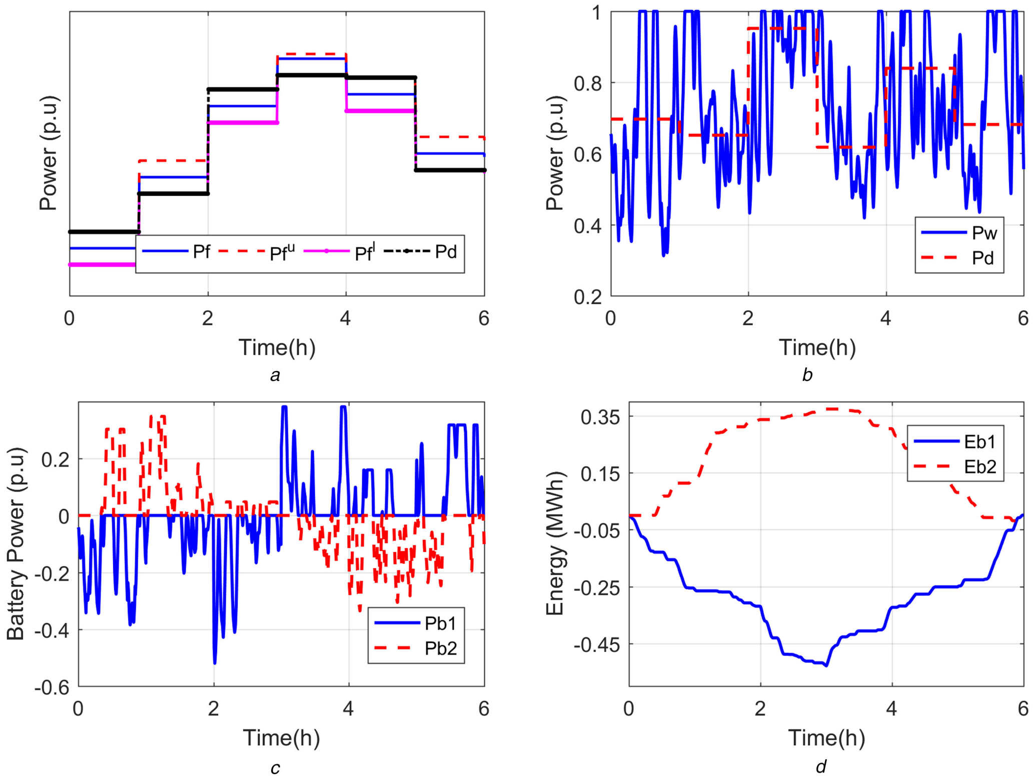

Fig. 5 *Short-term operation of proposed method considering prediction error*
(a) Determination of dispatched power, considering the prediction error, ***(b)*** Wind and dispatched power, ***(c)*** Battery power, ***(d)*** Battery energy level

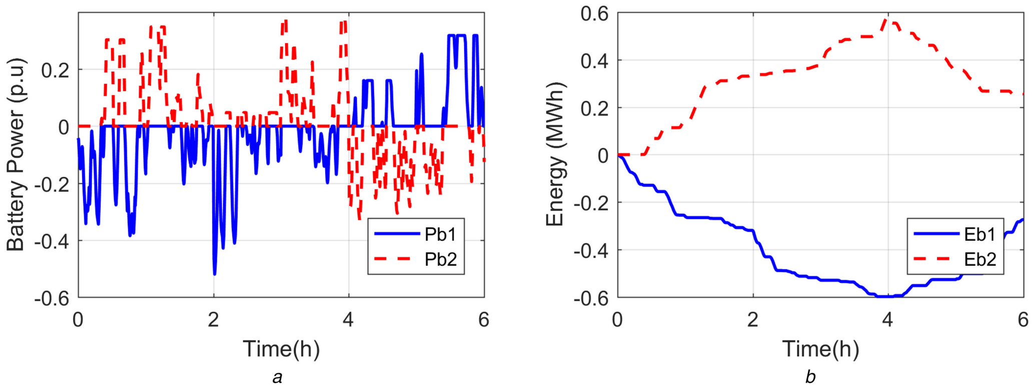

Fig. 6 *Balanced energy level with larger cycle time*
(a) Battery power, ***(b)*** Energy level

Table 2 Required battery power and energy capacity

	Without prediction error		With prediction error 10%	
	Battery power	Battery energy	Battery power	Battery energy
proposed method	0.6 MW	1.4 MWh	0.8 MW	2 MWh
second method	1.5 MW	3 MWh	2.2 MWh	5 MWh
first method	0.6 MW	1 MWh	0.8 MW	1.5 MWh

the energy level for both battery sets will be balanced in each half-cycle (Fig. 6*b*).

Overall, the prediction error leads to larger power and energy capacity that should be considered in planning phase.

5 Case study

In this section, battery sizing and short-time operation for a typical 2 MW wind turbine (rated wind speed: 12 m/s, cut-in and cut-out wind speeds 4 and 25 m/s, respectively) are investigated. First the planning phase, including battery sizing, is carried out and then the short-time operation is studied.

5.1 Battery sizing

5.1.1 Power capacity: A 2 years wind speed data [37] is assorted in 1 h intervals, then by considering upper and lower prediction errors of $\pm 10\%$, the dispatched power is determined for subintervals by using (18) and the proposed method in part (IV-B). As stated, the prediction error is dependent on prediction method and temporal and train type which is determined by prediction analysis. In this paper, artificial neural network method [34], considering 10% error is used for forecasting wind speed and wind power. After that the battery power for each interval is obtained from (1) and then using (2), the required power capacity is calculated and the results are shown in Table 2. In this table, the results of three methods in two cases; with and without prediction errors, are shown. As it is seen, the first and proposed methods need the same power capacity, while the second method requires about three times larger power capacity. In addition, it is shown that the prediction error leads to larger capacities in all three methods.

As it was mentioned, determination of the energy capacity is involved in a trade off with the lifetime. In this case, a 2 years lifetime with 750 charge cycles is assumed, so the entire period is divided by $N = 750$, which results in the duration time of $\Delta T = 2 * (8760/750) \simeq 24\,\text{h}$. Then according to (7) the required energy capacity is obtained for the second and the proposed methods. For the first method, it is obtained from (3). Results for the two conditions; with and without considering prediction error, are presented in Table 2 for the three methods. The required energy capacity in the proposed and the first methods is considerably lower than that of the second method. In addition the prediction error leads to larger capacities of BESS in all three methods.

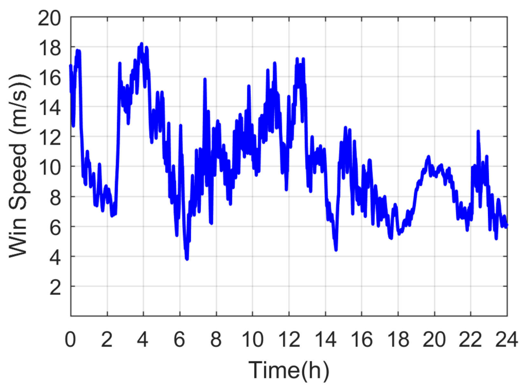

Fig. 7 *24 h wind speed profile*

5.2 Short term operation

In the operation phase, the battery power in each interval is obtained according to the proposed strategy. The SOC is kept at an allowable level ($\text{SOC}_L \le \text{SOC} \le \text{SOC}_H$). For a typical 24 h wind speed profile shown in Fig. 7, averaged over 10 min intervals, the results are obtained for a 2 MW wind turbine by employing the three mentioned methods.

Predicted wind power and the corresponding upper and lower limits, obtained from (16), are shown in Fig. 8. Results of the first and the proposed methods, which use the average value of forecasted power, are presented in Fig. 8*a* and those for the second method, using the max/min values of forecasted wind power during charge/discharge cycles, are given in Fig. 8*b*.

Then, according to the discussion made in Section 4, the dispatched power is selected between upper and lower forecasted powers alternatively for the first and the proposed methods (Fig. 9*a*) and the maximum/minimum values during discharging/charging cycles for the second method (Fig. 9*b*).

SOC for the two battery sets of the proposed method are shown in Fig. 10*a*. It is limited within the range $0.2 \le \text{SOC} \le 1$. When one of the batteries reaches the upper or lower limit, the mode of both batteries is interchanged. As it is seen, there is approximately one charge–discharge cycle for 24 h.

SOC for the second method is shown in Fig. 10*b*. It is seen that like the proposed method it has a complete charge/discharge cycle. It should be mentioned, however, in this case a BESS with larger capacity is required, as compared to the proposed method (Table 2).

SOC in the first method is shown in Fig. 10*c*, as it can be seen there are many shallow charge–discharge cycles which reduce the battery efficiency in terms of lifetime.

6 Conclusions

Unit commitment and participating in power market needs to commit a specific generation, several hours ahead. This is a big challenge for the intermittent and uncertain wind power. Using

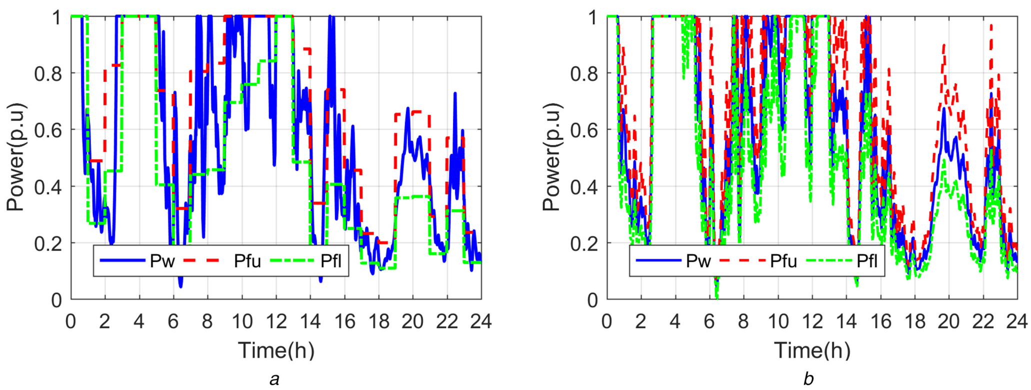

Fig. 8 *Results for a 2 MW wind turbine case study. Wind power and upper and lower forecasted values*
(a) First and proposed methods, ***(b)*** Second method

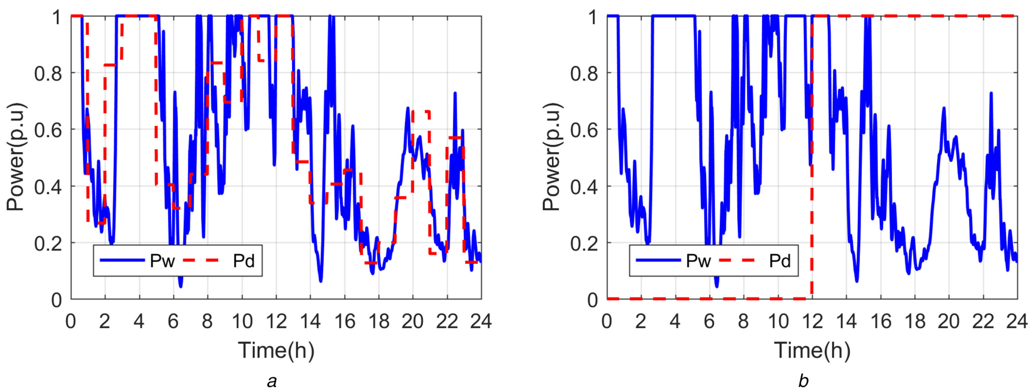

Fig. 9 *Results for a 2 MW wind turbine case study. Wind power and dispatched power*
(a) First and proposed methods, ***(b)*** Second method

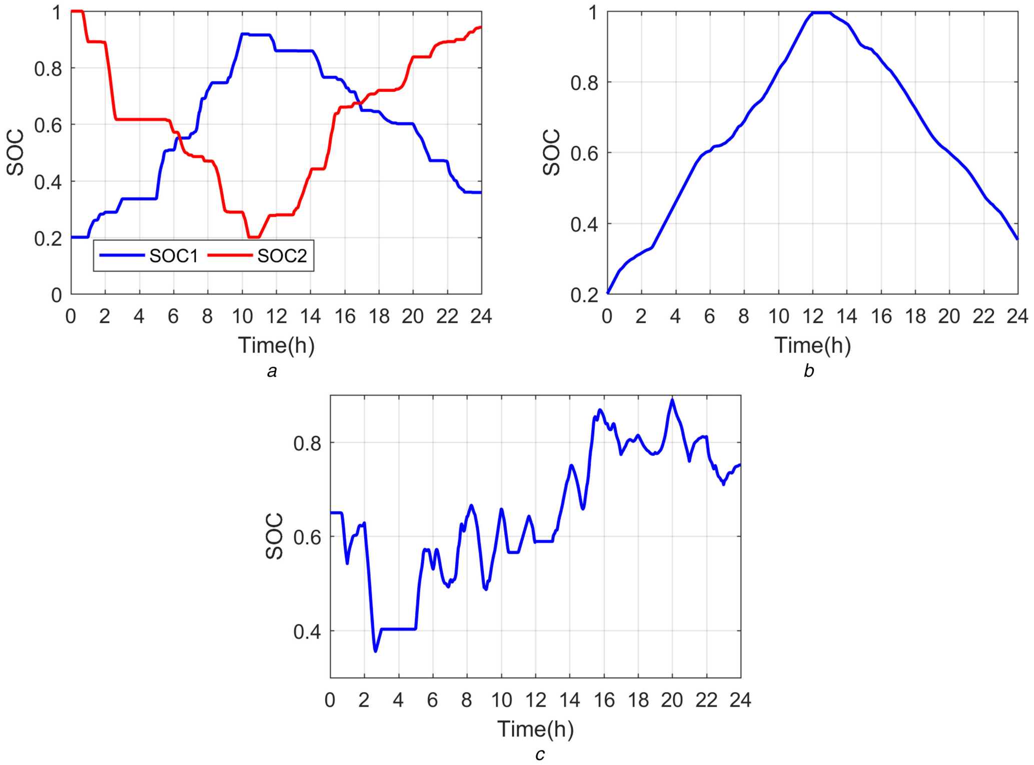

Fig. 10 *SOC*

(a) Proposed method, ***(b)*** Second method, ***(c)*** First method

BESS can compensate the prediction errors and power fluctuations during dispatching intervals. The proposed strategy in this paper uses mean value of wind power as the dispatched power. As the difference between the instantaneous wind power and its mean value is not large, the required battery capacity is low. Furthermore, in order to avoid many shallow charge–discharge cycles, two battery sets are used, which experience complete charge cycles, resulting in increased battery lifetime. Simulation results show the effectiveness of the proposed method in comparison with other methods. In addition, the short-term operation, considering the effect of prediction error, was investigated and it was shown that the prediction error leads to lager required power and energy capacity for BESS. The precision of prediction method and the spatial smoothing in wind farm can reduce the effects of prediction errors and power fluctuations, which in turn reduce the required power capacity for BESS. Since in this paper 10 min averaged data were used, the spatial smoothing in the wind farm was almost considered.

7 References

[1] Chen, Z., Blaabjerg, F.: 'Wind farm – a power source in future power systems', *Renew. Sustain. Energy Rev.*, 2009, **13**, (6-7), pp. 1288–1300

[2] Das, I., Bhattacharya, K., Canizares, C.: 'Optimal incentive design for targeted penetration of renewable energy sources', *IEEE Trans. Sustain. Energy*, 2014, **5**, (4), pp. 1213–1225

[3] Neguyen, N., Mitra, J.: 'An analysis of the effects and dependency of wind power penetration on system frequency regulation', *IEEE Trans. Sustain. Energy*, 2016, **7**, (1), pp. 354–363

[4] Shensi, S., Yue, Z., Zheng, L.*, et al.*: 'Grid code for wind power fluctuation in China and particle swarm optimization-based power dispatch solution', *J. Renew. Sustain. Energy*, 2015, **7**, p. 013118

[5] Chowdhury, M., Rao, M., Zhao, Y.*, et al.*: 'Benefits of storage control for wind power producers in power markets', *IEEE Trans. Sustain. Energy*, 2016, **7**, (4), pp. 1492–1505

[6] Morales, J.M., Conejo, A.J., Madsen, H.*, et al.*: '*Integrating renewables in electricity markets*', *International Series in Operations Research & Management Science*, vol. **205** (Springer, 2014)

[7] Elatar, E.E.: 'Prediction of wind power based on evolutionary optimised local general regression neural network', *IET Gener. Transm. Distrib.*, 2014, **8**, (5), pp. 916–923

[8] Huang, C., Kuo, C., Huang, Y.: 'Short-term wind power forecasting and uncertainty analysis using a hybrid intelligent method', *IET Renew. Power Gener.*, 2017, **11**, (5), pp. 678–687

[9] Wenxia, P., Bo, F., Jianhong, Z.: 'An analysis of capacity requirements of battery energy storage based on forecasted wind power correction'. Int. Conf. Sustainable Power Generation and Supply (SUPERGEN), Hangzhou, China, September 2012

[10] Lange, M.: 'On the uncertainty of wind power predictions – analysis of the forecast accuracy and statistical distribution of errors', *ASME, J. Sol. Energy Eng.*, 2005, **127**, (2), pp. 177–184

[11] Sorenson, P., Cutululis, N.A., Rodriguez, A.V.*, et al.*: 'Power fluctuations from large wind farms', *IEEE Trans. Power Syst.*, 2007, **22**, (3), pp. 958–965

[12] Kurian, S., Krishnan, S.T., Cheriyan, E.P.: 'Real time implementation of artificial neural networks-based controller for battery storage supported wind electric generation', *IET Gener. Transm. Distrib.*, 2015, **9**, (10), pp. 937–946

[13] Guo, L., Yu, Z., Wang, C.*, et al.*: 'Optimal design of battery energy storage system for a wind–diesel off-grid power system in a remote Canadian community', *IET Gener. Transm. Distrib.*, 2016, **10**, (3), pp. 608–616

[14] Li, X., Hui, D., Lai, X.: 'Battery energy storage station (BESS)- based smoothing control of photovoltaic (PV) and wind power generation fluctuations', *IEEE Trans. Sustain. Energy*, 2013, **4**, (2), pp. 464–473

[15] Lin, F.J., Chiang, H.C., Chang, J.K.*, et al.*: 'Intelligent wind power smoothing control with BESS', *IET Renew. Power Gener.*, 2017, **11**, (2), pp. 398–407

[16] Bizuayehu, A.W., Medina, P., Catalao, J.P.S.*, et al.*: 'Analysis of electrical energy storage technologies' state-of-the-art and applications on islanded grid systems'. Proc. IEEE PES T&D Conf. Expo., Chicago, IL, USA, 2014

[17] Jiang, Q., Wang, H.: 'Two-time-scale coordination control for a battery energy storage system to mitigate wind power fluctuations', *IEEE Trans. Energy Convers.*, 2013, **28**, (1), pp. 52–61

[18] Luo, F., Meng, K., Dong, Z.Y.*, et al.*: 'Coordinated operational planning for wind farm with battery energy storage system', *IEEE Trans. Sustain. Energy*, 2015, **6**, (1), pp. 253–262

[19] Yao, D.L., Choi, S.S., Tseng, K.J.*, et al.*: 'Determination of short term power dispatch schedule for a wind farm incorporated with dual battery energy storage scheme', *IEEE Trans. Energy Convers.*, 2009, **24**, (4), pp. 74–84

[20] Teleke, S., Baran, M.E., Huang, A.Q.*, et al.*: 'Control strategies for battery energy storage for wind farm dispatching', *IEEE Trans. Energy Convers.*, 2009, **24**, (3), pp. 725–732

[21] Wee, K.W., Choi, S.S., Vilathgamuwa, D.M.: 'Design of a least-cost battery-supercapacitor energy storage system for realizing dispatchable wind power', *IEEE Trans. Sustain. Energy*, 2013, **4**, (3), pp. 786–796

[22] Nguyen, C.L., Lee, H.H.: 'Effective power dispatch capability decision method for a wind-battery hybrid power system', *IET. Gener. Transm. Distrib.*, 2016, **10**, (3), pp. 661–668

[23] Li, Q., Choi, S.S., Yuan, Y.*, et al.*: 'On the determination of battery energy storage capacity and short-term power dispatch of a wind farm', *IEEE Trans. Sustain. Energy*, 2011, **2**, (2), pp. 148–158

[24] Jiang, Q., Gong, Y., Wang, H.: 'A battery energy storage system dual layer control strategy for mitigating wind farm fluctuations', *IEEE Trans. Power Syst.*, 2013, **28**, (3), pp. 3263–3273

[25] Nguyen, C.L., Lee, H.H., Chun, T.W.: 'Cost-optimized battery capacity and short-term power dispatch control for wind farm', *IEEE Trans. Ind. Appl.*, 2015, **51**, (1), pp. 595–606

[26] Fathima, A., Prabaharan, N., Palanisamy, K.: 'Sizing of VRB battery based on max-min method of power dispatch in a wind-PV hybrid system'. IEEE Conf. Energy Conversion (CENCON), Johor Bahru, Malaysia, 2015, pp. 221–226

[27] Abdullah, M.A., Muttaqi, K.M., Sutanto, D., *et al.*: 'An effective power dispatch control strategy to improve generation schedulability and supply reliability of a wind farm using a battery energy storage system', *IEEE Trans. Sustain. Energy*, 2015, **6**, (3), pp. 1093–1102

[28] Khatamianfar, A., Khalid, M., Savkin, A.V., *et al.*: 'Improving wind farm dispatching in the Australian electricity market with battery energy storage using model predictive control', *IEEE Trans. Sustain. Energy*, 2013, **4**, (3), pp. 745–755

[29] Kou, P., Gao, F., Guan, X.: 'Stochastic predictive control of battery energy storage for wind farm dispatching: using probabilistic wind power forecasts', *Renew. Energy*, 2015, **80**, pp. 256–300

[30] Yang, D., Wen, J., Chan, K., *et al.*: 'Dispatching of wind/battery energy storage hybrid systems using inner point method-based model predictive control', *Energies*, 2016, **9**, p. 629

[31] Bathurst, G.N., Weatherill, J., Strbac, G.: 'Trading wind generation in short term energy markets', *IEEE Trans. Power Syst.*, 2002, **17**, (3), pp. 782–789

[32] Yoshimoto, K., Nanahara, T., Koshimizu, G., *et al.*: 'New control method for regulating state-of-charge of a battery in hybrid wind power/battery energy storage system'. Power Systems Conf. and Exposition, Atlanta, GA, USA, 2006, pp. 1244–1251

[33] Drouilhet, S., Johnson, B.L.: 'A battery life prediction method for hybrid power applications'. The 35th AIAA Aerospace Sciences Meeting and Exhibit Reno, Nevada, 1997

[34] Ayodele, T.R., Ogomjuyigbe, A.S.O.: 'Prediction of wind speed for the estimation of wind turbine power output from site climatological data using artificial neural network', *Int. J. Ambient Energy*, 2015, **38**, (1), pp. 29–36

[35] Sideratos, G., Hatziargyriou, N.D.: 'An advanced statistical method for wind power forecasting', *IEEE Trans. Power Syst.*, 2007, **22**, (1), pp. 258–265

[36] Bendat, J.S., Piersol, A.G.: '*Random data; analysis and measurement procedures*' (Wiley Press, New Jersey, 2010, 4th edn.)

[37] Brekken, T.K.A., Yokochi, l., von Jouanne, A., *et al.*: 'Optimal energy storage sizing and control for wind power applications', *IEEE Trans. Sustain. Energy*, 2011, **2**, (1), pp. 69–77