Coordinated Operational Planning for Wind Farm with Battery Energy Storage System

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***Abstract*—This paper proposes a coordinated operational dispatch scheme for wind farm with battery energy storage system (BESS). The main advantages of the proposed dispatch scheme are that it can reduce the impacts of wind power forecast errors while prolonging the lifetime of BESS. The scheme starts from planning stage, where a BESS capacity determination method is proposed to compute the optimal power capacity and energy capacity of BESS based on historical wind power data; and then, at operation stage, a flexible short-term BESS-wind farm dispatch scheme is proposed based on the forecasted wind power generation scenarios. Three case studies are provided to validate the performance of the proposed method. The results show that the proposed scheme can largely improve the wind farm dispatchability.**

***Index Terms*—Battery energy storage system, Renewable energy, Wind farm dispatch**

NOMENCLATURE

Wind Farm and BESS Parameters

t , T	Index and total number of time intervals;
Δt	Time duration of each time interval;
P_{wind}^t	Power output of wind turbines at time *t* (MW);
P_{ref}^t	Referenced power output of wind farm at time *t* (MW);
P_{BESS}^t	Power output of BESS at time *t* (MW);
P_{WF}^t	Total power output of wind farm at time *t* (MW);
$P_{BESS}^{Chr,Max}$, $P_{BESS}^{Dis,Max}$	Maximum charge and discharge power limit of BESS (MW);
SOC^t	State-of-charge (SOC) of BESS at time *t*;
SOC^{Min} , SOC^{Max}	Lower and upper SOC limit of BESS;
E_{BESS}^t	Energy stored in BESS at time *t* (MWh);
E_{BESS}^r	Rated energy capacity of BESS (MWh);
η_c , η_l	The charging loss (%) and leakage loss factors (%/month) of BESS;
v , v_0	Upstream and downstream wind speed (m/s);
ρ	Air density (kg/m^3);
r	Turbine rotor radius (m);
v_{in} , v_{out}	Cut-in and cut-out wind speeds (m/s);

Wind Power Forecast Error Fitting Parameters

$pdf_i\left(P\right)$	Wind power output distribution function of bin *i*;
α_i , β_i	Probability distribution parameters of bin *i*;
μ_i , σ_i	Mean value and variance of bin *i*;
p_1 , p_2	Approximation parameters;
$pdf\left(\varepsilon\right)$	Wind power forecast error distribution;
$\omega(i)$	Weight of bin *i*;
L	Energy loss of BESS;
$\overline{P}$	Long-term mean wind power generation (MW);
L_0	Maximum allowable energy loss limit;

Wind Farm NPV Calculation Parameters

g	Annual general inflation (%);
I	Annual interest rate (%);
Y	Simulation period (years);
NPC_{r_BESS}	Discounted present costs of future costs of replacing the batteries throughout the simulation period ($);
C_{pur_BESS}	Purchase cost of BESS;
LT_{BESS}	Lifespan of BESS (years);
N_{rep_BESS}	Number of replacements of batteries during the simulation period;
$C_{O\&M\_BESS}$	Annual cost of operation and maintenance of BESS ($/year);
$NPC_{O\&M\_BESS}$	Discounted present costs of future costs of operation and maintenance of BESS throughout simulation period ($);
NPV_{sale_power}	Discounted present values of income from the sale of wind power to grid ($);
PR_{power}	Procumbent price of wind power ($/MWh);

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E_{wf_yr}	Annual electricity sold to grid generated by wind farm (MWh/year);
NPV_{res}	Discounted present costs of future costs of replacing batteries throughout simulation period ($).

I. Introduction

As one of most popular renewable energy resources, wind energy has gained widespread concerns in recent years [1]. With the introduction of various emission reduction schemes, increasing number of wind plants have been planned or installed around the world [2]. These policies are expected to underpin solid progress of wind energy industry. In Australia, the wind market is benefiting from favorable tax treatment and state mandates for renewable energy. It is expected that wind energy will provide the largest share of Australia's targeted 20% renewable energy by 2020 [3]. However, due to its stochastic nature, the integration of wind energy into power grid has become one of the biggest challenges for system operation. Variations of wind speed directly influences the power generation, which means the output of fossil fuel-plants needs to be adjusted more frequently to mitigate the fluctuations, and this also causes difficulties in estimating suitable system reserve to ensure secure and reliable operation. Therefore, high penetration of wind power may cause high potential risks and difficulties in system operations [4].

Recent advances in energy storage technologies provide an opportunity for utilizing energy storage devices to address the intermittency of renewable energy resources. Compared with other technologies, BESS is the most cost-effective option for short-term wind farm dispatch purposes. Combining BESS with wind farm can not only improve system availability, but also increase the amount of wind power that can be penetrated into power grid without risking system reliability. Various methods have been proposed to coordinate BESS and wind farm to increase wind power penetration levels. Some researches focus on BESS-wind farm control issues. A hybrid STATCOM-BESS control approach was proposed in [5],[6] to improve system stability as well as power quality. In [7], a washout filter-based scheme was proposed to smooth out short-term power fluctuations of a wind farm with vanadium redox-flow batteries. In [8], the control scheme proposed in [7] was improved to incorporate more constraints, so that BESS can be used to smooth the net power exported to power grid for short-term dispatch purposes. A control scheme was proposed to adjust battery charging and discharging current over a given period [9], in order to minimize the gaps between the referenced and the actual battery power outputs. These studies mainly focused on the controller design for BESS-wind farm system, without addressing the issues of battery capacity determination and short-term dispatch scheme. Moreover, the frequent change between charge and discharge modes will shorten the lifetime of BESS, which is not considered in these designs either.

Some other works study the short-term dispatch scheme for BESS-wind farm system. In [10], decision tree based real-time dispatch strategy was proposed to control BESS power output. In [11], two models were compared to determine the size of grid BESS and the dispatch in a wind-diesel system with hydrogen storage. To reduce the fluctuation impacts of wind power, a dual BESS-wind farm system was proposed for short-term dispatch in [12]-[14], which include an in-service battery and a stand-by battery. When the stand-by battery is charged by the power generated by wind turbine, the in-service battery provides constant power output to the grid. The two units interchange their roles when the one in-service reaches operational limits. By employing the dual-BESS scheme, the battery in-service can aggregate the dispatchable energy and makes wind farm act as conventional generator. However, the major limitation of this scheme is the high capital cost. Since the BESS-wind farm system power output to the grid is completely from the battery in-service and all the energy produced by the wind turbines is stored in the stand-by battery, which means a large capacity of each battery is required.

Motivated by the works in [12]-[14], in this paper we propose a novel coordinated operational dispatch scheme. The proposed strategy can mimic the behavior of the dual BESS-wind farm system to some extent by using single BESS. Instead of change between in-service and stand-by batteries, the proposed scheme improves wind farm dispachability by adjusting power output between higher and lower levels. Compared with other single BESS-wind farm systems, the proposed scheme can stabilize wind farm power output and reduce the impacts of wind forecast errors more effectively; compared with the dual BESS-wind farm system, the proposed scheme requires lower capital cost and it can be implemented more easily. In addition, a method for determining the optimal capacity of BESS under the proposed dispatch scheme is proposed as well.

The paper is organized as follows. The wind power forecast toolbox utilized in this paper is introduced in Section II; the proposed coordinated dispatch scheme is described in Section III; the BESS capacity determination methodology is presented in Section IV; simulation studies are given in Section V; finally, conclusions are drawn in Section VI.

II. Wind Power Forecast Toolbox

Wind forecast is a basic task to facilitate renewable penetrations [15],[16]. The forecast toolbox, *OptiWind* [17], is used for wind speed forecast in this paper. *OptiWind* incorporates highly customized numerical weather prediction models and latest statistical methods together. Several important factors are considered in the prediction model, including temperature, seasonal weather, public holidays, historical wind data, and etc. And the mean absolute error (MAE) is used to evaluate the forecast accuracy.

$$MAE = \frac{1}{N_h}\sum_{p=1}^{N_h} | v - \overline{v} | \times 100\% \tag{1}$$

where, N_h is the sampling quantity; v is the actual speed; and $\overline{v}$ is the forecasted speed. The comparisons of forecasted and actual wind speed are shown in Fig. 1.

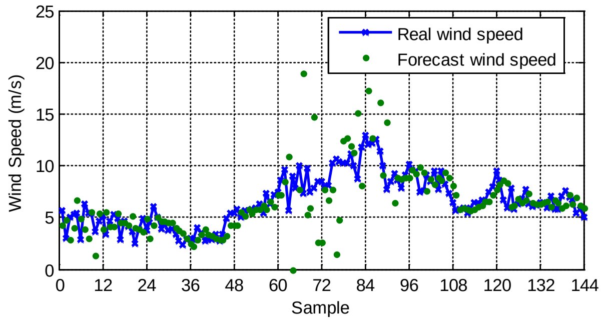

Fig. 1. Wind speed forecast results

The forecasted wind power is converted from kinetic energy by wind turbine and the output strongly depends on the wind speed. The wind turbine output power is given by [18],

$$P_M = \frac{1}{2}\pi r^2 \rho v^3 \frac{\left(1+\frac{v_0}{v}\right)\left[1-\left(\frac{v_0}{v}\right)^2\right]}{2} \tag{2}$$

$$P_{Wind} = \begin{cases} 0, & v_0 < v_{in} \\ P_M, & v_{in} \le v_0 \le v_{out} \\ 0, & v_{out} < v_0 \end{cases} \tag{3}$$

The wind power is controlled through rotor speed by maximum power point tracking method. Meanwhile, the pitch angle of the blade can be controlled to adjust wind turbine output. There is no power generated at wind speeds below cut-in speed or above cut-out speed; at wind speeds between cut-in speed and cut-out speed, the output can be calculated by Eq. (2).

III. Dispatch Scheme for Wind Farm with BESS

Due to its intermittency nature, the large-scale integration of wind power into electric grids may jeopardize system stability and reliability. Therefore, to stabilize wind farm power output, BESS is utilized to compensate the fluctuations and make wind farm output follows pre-defined dispatchable reference [7]-[9]. The outline of a BESS-wind farm studied in this paper is shown in Fig. 2.

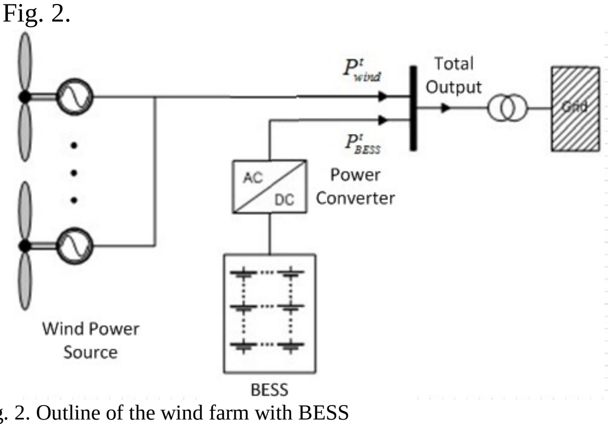

Fig. 2. Outline of the wind farm with BESS

Denoting P^t_{ref} as the referenced power output of wind farm at time t, the P^t_{BESS} is calculated by,

$$P^t_{BESS} = P^t_{ref} - P^t_{wind} \tag{4}$$

In this section, BESS operational constraints are introduced firstly, followed by the BESS short-term dispatch scheme. Finally, the methodology for determining BESS capacity is presented, which relies on the short-term dispatch scheme.

A. BESS Operational Constraints

The operation of BESS is subjected to the following constraints,

(1) Power limits

$$P^{Chr,Max}_{BESS} \le P^t_{BESS} \le P^{Dis,Max}_{BESS} \tag{5}$$

(2) SOC limits

$$SOC^{Min} \le SOC^t \le SOC^{Max} \tag{6}$$

The SOC^t and energy changing of BESS are calculated as Eqs. (7) and (8).

$$SOC^t = E^t_{BESS} / E^r_{BESS} \tag{7}$$

$$E^{t+1}_{BESS} = E^t_{BESS} + \Delta t \cdot P^t_{BESS} - |P^t_{BESS}| \cdot \eta_c \cdot \Delta t - E^t_{BESS} \cdot \eta_l \cdot \Delta t \tag{8}$$

B. Coordinated Short-Term Dispatch Scheme

1) Dispatch Principles

The proposed dispatch principles are shown in Fig. 3. Firstly, to overcome the uncertainties in wind generation, three wind power output scenarios are forecasted using interval prediction, *pessimistic wind power scenario*, *normal wind power scenario*, and *optimistic wind power scenario*, which are denoted as S_L, S_M, and S_H. To mitigate the fluctuations of wind farm output, S_L and S_H are averaged on hourly basis, depicted by the top and bottom curves in Fig. 3. By charging and discharging BESS, the final referenced power output of wind farm P_{ref} is then scheduled to switch between S_L and S_H. In other words, P_{ref} changes between the higher level and lower level power outputs, alternatively. BESS is scheduled to determine the switch time points between S_L and S_H, and make the actual wind farm power output follows P_{ref}.

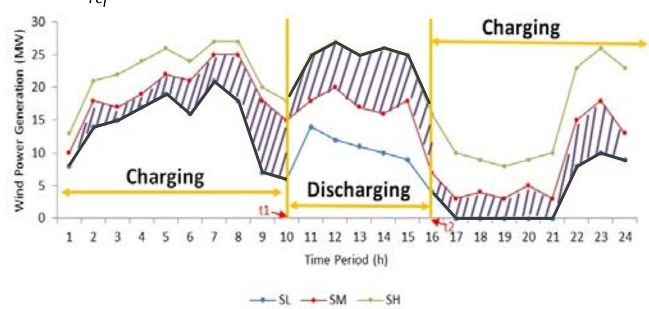

Fig. 3. Dispatch scheme of BESS

Relying on the state-of-the-art short-term wind speed forecast techniques, it can be expected that the actual wind power will be close to S_M with certain deviations. t_1, t_2,… in Fig. 3 represent the time points when P_{ref} switches between S_L and S_H. During this process, the battery is charged or discharged within operational constraints. For example, assume BESS is at SOC lower limit in the beginning, and the corresponding P_{ref} is S_L until t_1. Because the actual wind power output will be closed to S_M, the BESS is charged until t_2, when the BESS reaches its SOC upper limits. Afterwards, P_{ref} is switched to S_H, and the BESS starts discharge process. During the period from t_1 to t_2, the gap between S_H and S_M is compensated by the BESS. The charging and discharging process continues alternatively.

2) Impacts on BESS Lifetime

The lifetime of BESS is normally quantified by a number of charge cycles [20],[21]. Under traditional schemes, where the forecasted wind power is directly smoothed on hourly basis to produce s single referenced power output curve [7],[8], BESS needs to be charged/discharged frequently to compensate the gaps between the actual and the referenced power generation. This will lead to large number of charge/discharge cycles and shorten the lifetime of BESS. Such frequent switches may also cause power quality issues. However, in the proposed scheme, the BESS-wind farm switches the referenced curve between S_H and S_L, and the BESS is regularly charged and discharged. Its charge/discharge cycles can be significantly reduced and lifetime can be prolonged. Therefore, during the whole project, fewer BESSs are required and the investment can be reduced. The medium-term benefits can be formed by accumulation of short-term operation saving.

3) Practical Operation Considerations

After participating in system dispatch, wind farm operators need to submit generation schedules to the independent system operator, which means the referenced wind farm power generation should be determined day-ahead or hours-ahead. Due to the uncertainties in wind forecast, the predictions normally have some errors. Therefore, in real-time operation, wind farm will be penalized if it is overestimated or underestimated in the first *x* hours. The generation schedule after the first *x* hours can be adjusted by wind farm operators governed by market rules [13].

When applying the proposed dispatch scheme in practical applications, actual wind farm output should follow the referenced power curve in the first *x* hours. In the dual-BESS solution, this is achieved by setting the scheduled power output of the in-service battery to lower level output [12]-[14]. Correspondingly, in our proposed scheme, this can be easily achieved by setting the referenced wind farm output of first *x* hours to be S_L. The wind farm operator is then allowed to adjust the referenced wind power output after first *x* hours. Same as calculating the switch time of in-service and standby batteries in [13], in the proposed scheme, the wind farm operators can estimate the switch time between S_L and S_H. Specifically, for the first *x* hours, the referenced wind farm power output is S_L and the battery is charged. Then, by utilizing the online wind power forecasting and online battery SOC monitoring, the wind farm operator can estimate the remaining time to reach the battery SOC upper limit after first *x* hours (t_1 in Fig. 3). Then, the wind farm operator can re-schedule the wind farm referenced power beyond the first *x* hours. Under normal market rules, this re-schedule cycle can be typically half-hour or one hour. Similar to [11]-[13], the practical operation of the proposed scheme requires online monitoring of the BESS SOC. This can be achieved by employing the commercial SOC monitoring devices.

IV. BESS Capacity Determination Methodology

The main trade-off in battery selection is between power capacity and energy capacity. In this section, the methodology for determining the BESS capacity under the proposed dispatch scheme is presented. It should be noted that the results acquired through the following approaches are theoretically optimal. In the market, batteries are classified into specific capacity levels according to different manufacturers. To make the study become more practical, after obtaining the theoretically optimal results, the closest product available in the market will be selected in the case study.

A. BESS Power Capacity Determination

Since the power capacity of BESS cannot be large enough to satisfy all the wind conditions, determining the optimal power capacity of BESS is an important issue in wind farm planning. As indicated in [19], large wind power errors are rare and if a certain energy loss is allowed, the installed power capacity of BESS can be significantly reduced. In this paper, by considering the stochastic nature of wind resource, the BESS power capacity is calculated based on the distribution of wind forecast errors [19].

The long-term wind power [*measured, forecasted*] data pairs are sorted in *n* bins. The bin width is *1/n* p.u. For example, if *n* is set to 50, then the bin width is 0.02 p.u. It is assumed that in each bin, all measured values have the same forecast $P_{p,i}$, which is the mean value of all the calculated forecasts corresponding to bin *i*. Then, the measured power distribution within bin *i*, denoted by $pdf_i(P)$, is fitted as Beta distribution in Eqs. (9) and (10).

$$pdf_i(P) = \frac{P^{\alpha_i - 1}(1-P)^{\beta_i - 1}}{B_i(\alpha_i, \beta_i)} \tag{9}$$

$$B(\alpha_i, \beta_i) = \int_0^1 P^{\alpha_i - 1}(1-P)^{\beta_i - 1} dP \tag{10}$$

where, *P* is the measured wind power in p.u.. The values of α_i and β_i are calculated from μ_i and σ_i^2,

$$\alpha_i = \frac{(1-\mu_i)\mu_i^2}{\sigma_i^2} - \mu_i \tag{11}$$

$$\beta_i = \frac{1-\mu_i}{\mu_i} - \sigma_i \tag{12}$$

According to [19], σ_i is calculated by the approximation function in Eq. (13) instead of directly using the variance.

$$\sigma_i = \sqrt{\mu_i(1-\mu_i)\left(-p_2\mu_i^2 + p_1\mu_i\right)} \tag{13}$$

where, p_1 and p_2 are approximation parameters. For each bin, after fitting the *pdf* of the measured power, the error distribution of can be calculated by subtracting $P_{p,i}$ from the amplitude axis of the *pdf*. Then the total forecast error distribution, $pdf(\varepsilon)$, is obtained by weighted adding up the *pdf*s of all bins, shown in Eq. (14).

$$pdf(\varepsilon) = \sum_{i=1}^{n} \omega(i)\, pdf(\varepsilon_i) \tag{14}$$

Based on the distribution of forecast error, the energy loss of BESS can be calculated as the function of BESS nominal capacity and in terms of the long-term mean wind power.

$$L = \frac{1}{\bar{P}} \int_{P_{BESS}}^{1} pdf(\varepsilon)(\varepsilon - P_{BESS}) d\varepsilon \tag{15}$$

The nominal power capacity of BESS, P_{BESS} can be calculated by setting $L \le L_0$, where L_0 is the predefined energy loss limit [19].

B. BESS Energy Capacity Determination

In the proposed dispatch scheme, the larger the BESS energy capacity, the fewer the charge/discharge cycles, the longer the BESS lifetime, the higher the maintenance & operation costs [13]. In this paper, we determine the optimal BESS energy capacity by performing long-term economic analysis of different BESSs based on historical data. The optimal BESS energy capacity is selected as one which maximizes net present value (NPV) [20] [21]. For simplicity, in this paper, we only consider the battery related costs. More factors can be integrated easily if required, such as inverter/rectifier investment cost, land acquisition cost, and etc.

1) Cost

The costs of wind farm include two parts,

• Discounted present costs of future costs of replacing the battery [20]. The acquisition cost of the batteries will increase in accordance with general inflation *g*. The discounted present costs of future costs for the replacement of the batteries is calculated as

$$NPC_{r\_BESS} = \sum_{i=1}^{N_{rep\_BESS}} C_{pur\_BESS} \frac{(1+g)^{i\cdot LT_{BESS}}}{(1+I)^{iLT_{BESS}}} \tag{16}$$

where, N_{rep_BESS} is obtained as Eq. (17).

$$N_{rep\_BESS} = \mathrm{int}\left[\frac{Y}{LT_{BESS}}\right] \tag{17}$$

• Discounted present costs of future costs of operation and maintenance (O&M) of batteries through the simulation period [20].

$$NPC_{O\&M\_BESS} = \sum_{y=1}^{Y} C_{O\&M\_BESS} \frac{(1+g)^{y}}{(1+I)^{y}} \tag{18}$$

2) Income

In this study, we assume that the power generated by wind farm will be sold back to grid at a fixed procumbent price. The income consists of two parts,

• Discounted present values of the income by the sale of electricity generated by the wind farm.

$$NPV_{sale\_power} = \sum_{y=1}^{Y} PR_{power} E_{wf\_yr} \frac{(1+g)^{y}}{(1+I)^{y}} \tag{19}$$

• Discounted present values of income for residual value of the battery at the end of simulation period [20], which is proportional to the remaining lifespan of the battery.

$$NPV_{res} = C_{pur\_BESS}\left[1-\frac{N_{rep}LT_{BESS}}{Y}\right]\frac{(1+g)^{y}}{(1+I)^{y}} \tag{20}$$

3) Net Present Value

The NPV of the wind farm is calculated by Eq. (21).

$$NPV = NPV_{sale\_power} + NPV_{res} - NPC_{r\_BESS} - NPC_{O\&M\_BESS} \tag{21}$$

4) Battery Lifetime Calculation

In this paper, the average equivalent full cycles method is used to calculate the lifetime of BESS [21]. This method estimates the battery lifetime through cycles to failure. Using this method, the equivalent full cycles is defined as the number of cycles to failure multiplied by the depth of discharge of BESS. The average of equivalent full cycles is the value that is used to calculate the life of batteries.

V. SIMULATION STUDY

In this study, the Li-ion battery is selected due to its better performance when compared with other types of batteries [21]. The parameters in the simulation are given in Table I.

TABLE I
SIMULATION PARAMETER SETTING

BESS Operational Limits	
SOC upper limit (%)	80
SOC lower limit (%)	20
Initial SOC of BESS (%)	80
Wind Power Forecast Error Fitting	
Number of bins	50
p_1	0.1
p_2	0.1
L_0 (%)	4
Wind Farm NPV Calculation	
C_{pur_BESS}	120
$C_{O\&M\_BESS}$	2
PR_{power}	0.5
g	2
I	4
Y	20
Equivalent Full Cycles	1200
Short-Term Dispatch	
Dispatch Horizon (hour)	24
Smooth Interval (minute)	60

C. Tested Wind Farm

The historical data of a wind farm consisting of 30 Vestas V52 850 kW wind turbines is used in the case study [18]. The installed power capacity of this wind farm is 25.5 MW. The cut-in, cut-out, and rated speeds of this type of turbine are 4 m/s, 25 m/s, and 17 m/s, respectively. The wind speed distribution and Weibull fitting are shown in Fig. 4.

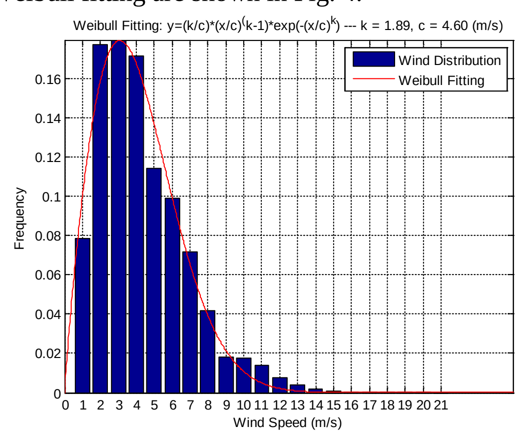

Fig. 4. Wind speed distribution and Weibull fitting

D. BESS Power Capacity Determination

To determine the BESS power capacity, the distribution of wind power forecast error should be fitted in advance. The fitted beta distributions of random selected ten different bins and the total forecasted error distribution are shown in Figs. 5 and 6. Then, according to Eq. (8), the minimum BESS power capacity for the studied wind farm is determined as 4.9 MW, which is about 19% of the installed power capacity. Therefore, for practical applications, the power capacity is chosen as 5 MW.

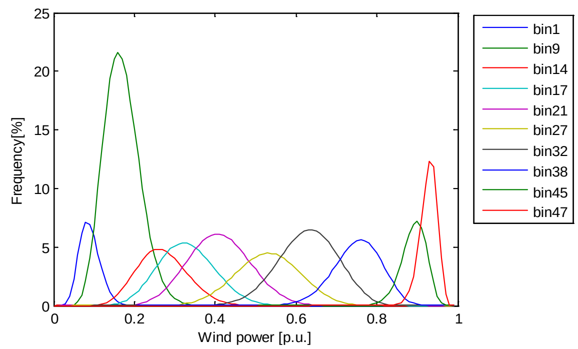

Fig. 5. Approximated Beta distribution of 10 random selected bins

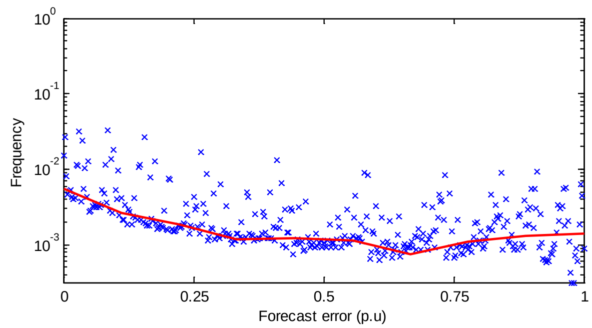

Fig. 6. Approximated Beta distribution of the total wind power forecast errors

E. BESS Energy Capacity Determination

The choices of 5 MW power capacity BESSs in the market is limited. According to DOE global energy storage database, four different power/energy ratios are selected [22]. To namely, 2 hours, 3 hours, 4 hours, and 6 hours, which are shown in Table II. Based on the historical wind data and Eq. (10), the NPV over 20 years are evaluated for each option in TABLE II. The results are shown in Fig. 7. The BESS with [5 MW, 20 MWh] is finally selected for the tested wind farm.

TABLE II
TYPICAL POWER/ENERGY RATIOS OF LI-ION BESS

Company	Power/Energy Ratio
BYD Auto	6 hours
ATL	4 hours
Aviation	3 hours
Wangxiang	2 hours

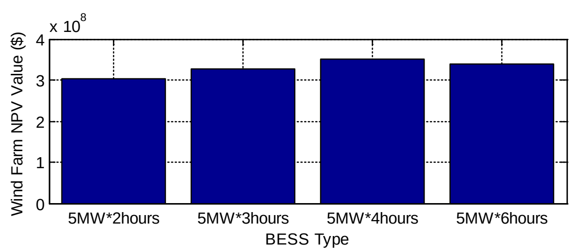

Fig. 7. Wind farm NPV comparison of different BESS energy capacities

F. Short-Term Dispatch

Three case studies are applied to evaluate the performance of the proposed strategy. The first case represents the ideal scenario where the normal wind power forecast is the same as the actual wind power. The other two cases represent the scenarios where the forecast wind power significantly deviates from the actual wind power series. In all these three cases, the proposed scheme is compared with the single referenced power scheme where the BESS is used to compensate the wind farm referenced power directly. A fluctuation degree value (*FDV*) in Eq. (22) is applied to evaluate the fluctuation degree of wind farm power output.

$$FDV = \sum_{t=1}^{T} \sqrt{\left(P_{wf}^{t} - P_{ref}^{t}\right)^{2}} \tag{22}$$

1) Case1

In this case, the actual wind power is the same as the normal forecasted wind power. The three different forecast scenarios are shown in Fig. 8. The referenced and actual wind farm output profiles are shown in Fig. 9.

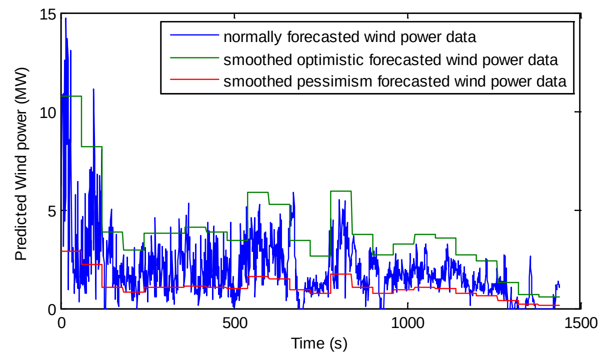

Fig. 8. Three day-ahead wind power generation forecast scenarios of case 1

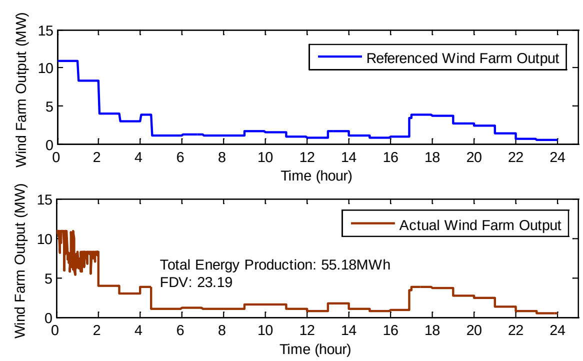

Fig. 9. Wind farm power outputs under the proposed scheme of case 1

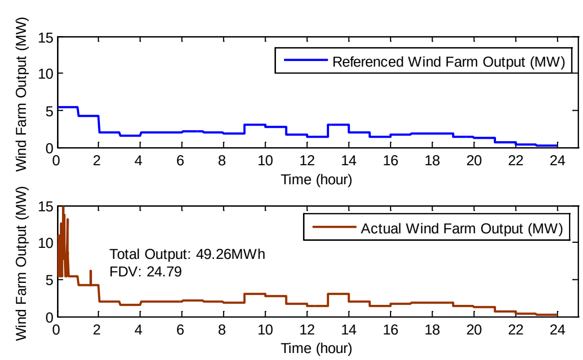

Fig. 10. Wind farm power outputs under single referenced scheme of case 1

For comparison purposes, the wind farm output under single referenced power scheme is shown in Fig. 10. We observe the SOC profiles under both schemes, which are shown in Fig. 11.

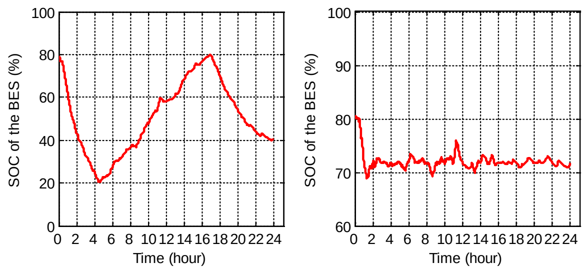

Fig. 11. SOC profiles under the proposed scheme (left) and single referenced power scheme (right) of case 1

The *FDV*s of both schemes are nearly the same, with 23.19 and 24.79, respectively. Under the proposed scheme, the wind farm produces more energy than the single referenced power scheme (55.18 MWh vs. 49.26 MWh). This is because the proposed scheme utilized the initial pre-stored energy by discharging the battery and raising the wind farm referenced power output firstly. The single referenced power scheme does not use the pre-stored energy and the SOC dramatically fluctuates between approximately 69% and 81%. Also, it can be seen the SOC profile of the BESS under the proposed scheme follows a regular charging/discharging with some minor fluctuations.

2) Case2

Case 2 represents the scenario where the wind generation is overestimated. The forecasted and actual wind power data are shown in Fig. 12. The dispatch results of the proposed scheme and single referenced power scheme are shown in Figs. 13, 14 and 15.

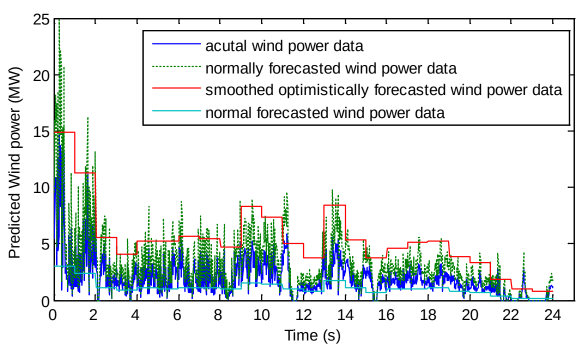

Fig. 12. Three day-ahead wind power generation forecast scenarios of case 2

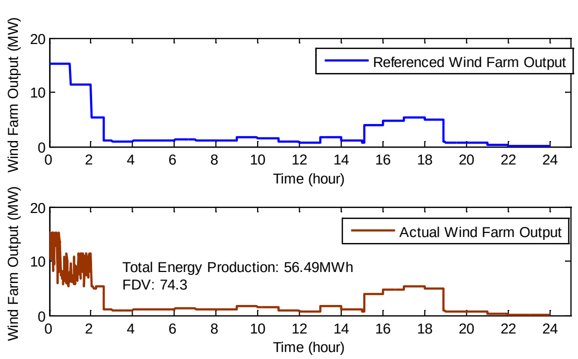

Fig. 13. Wind farm power outputs under the proposed scheme of case 2

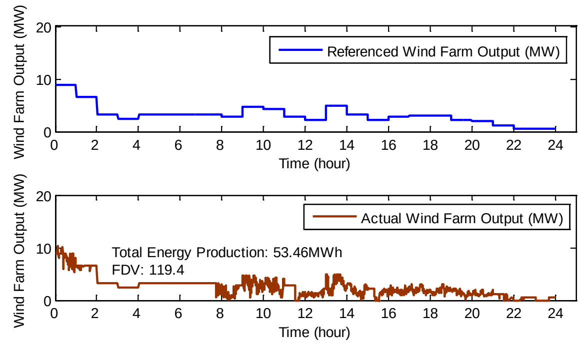

Fig. 14. Wind farm power outputs under single referenced scheme of case 2

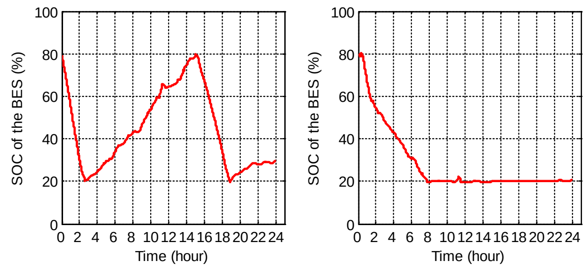

Fig. 15. SOC profiles under the proposed scheme (left) and single referenced power scheme (right) of case 2

Under the proposed scheme, the total output (56.49 MWh) is just slightly less than that of the single referenced power scheme (53.46 MWh). This is because when the battery discharges until its SOC lower limit, the wind farm switches to the lower level output mode until the end of the dispatch horizon. Also, it can be clearly seen that, the proposed scheme stabilizes the wind farm output significantly, with FDV values are 74.3 and 119.4. The SOC profiles show that under the single referenced power scheme, the battery exhausted after about 8 hours and then out of service. While under the proposed scheme, the battery keeps serving to compensate the wind farm output fluctuations.

3) Case3

The forecasted and actual wind power data are shown in Fig. 16, where the wind generation is underestimated. The dispatch results of the proposed scheme and single referenced power scheme are shown in Figs. 17, 18 and 19.

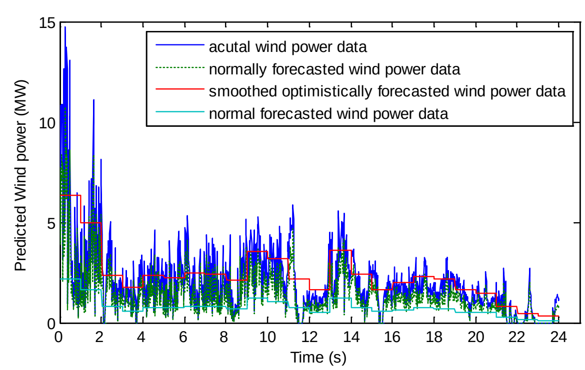

Fig. 16. Three day-ahead wind power generation forecast scenarios of case 3

The wind farm under the proposed scheme generated more energy than the single referenced power scheme, (57.27 MWh vs. 48.22 MWh). The FDV of the wind farm under the proposed scheme is just 5.06, while that under the single referenced power scheme is 87.83. This indicates that under the proposed scheme, the output of wind farm exactly follows the referenced output. The SOC profiles indicate that under the proposed scheme, the battery is kept being discharged; under the single referenced power scheme, the battery is disabled from being further charged beyond SOC upper limits most of the time.

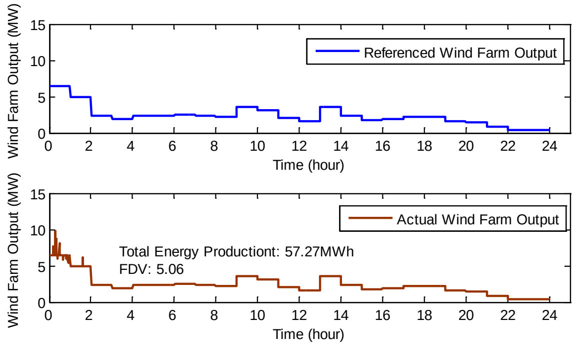

Fig. 17. Wind farm power outputs under the proposed scheme of case 3

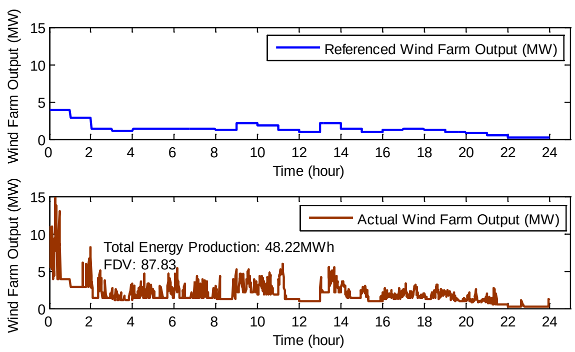

Fig. 18. Wind farm power outputs under single referenced scheme of case 3

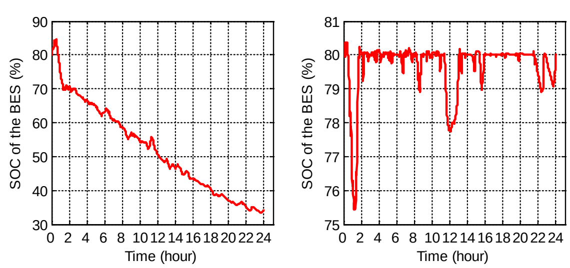

Fig. 19. SOC profiles under the proposed scheme (left) and single referenced power scheme (right) of case 3

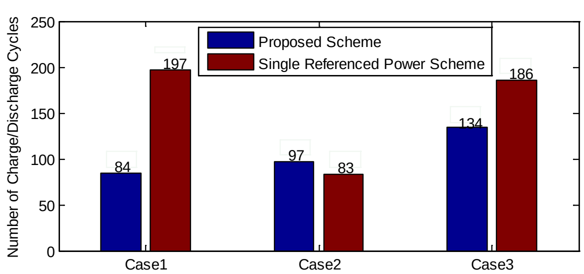

Fig. 20. Charge/discharge cycles comparison of both dispatch schemes

It is worth noting that the simulation results clearly show that the number of BESS charge/discharge cycles under the proposed scheme is much less than that of the single referenced power scheme. The comparison of the counted charge/discharge cycles of both schemes is shown in Fig. 20. In case 2, the number of BESS charge/discharge cycles under the proposed scheme is slightly larger, this is because in the single referenced power scheme, the BESS is kept being discharged and finally exhausted. After that, there is no further charge/discharge actions are performed on the BESS. However, case 1 and case 2 requires fewer charge/discharge cycles in the proposed scheme.

VI. Conclusions

A novel coordinated operational dispatch scheme for BESS-wind farm with is proposed in this paper. By changing the referenced wind farm power output between optimistic and pessimistic forecasted scenarios, this scheme can better mitigate the fluctuation and stochastic nature of wind resources. The BESS capacity determination issue is also addressed in this paper based on historical wind data. The optimal power capacity of the BESS is determined based on fitting the statistical analysis of wind power forecast errors distributions, and the optimal BESS energy capacity is determined by calculating the NPV with different energy capacities. Three cases are designed for the short-term dispatch. The simulation results prove the efficiency of the proposed scheme.

References

[1] F. Yao, Z.Y. Dong, K. Meng, Z. Xu, H. Iu, and K.P. Wong, "Quantum-inspired particle swarm optimization for power system operations considering wind power uncertainty and carbon tax in Australia," *IEEE Trans. Ind. Inform.*, vol. 8, no. 4, pp. 880–888.

[2] Z.Y. Dong, K.P. Wong, K. Meng, F.J. Luo, F. Yao, and J.H. Zhao, "Wind power impact on system operations and planning," *IEEE PES Gen. Meeting*, Minneapolis, USA, Jul. 2010.

[3] Renewable Energy Target, Australian Government Clean Energy Regulator, [Online]. Available: http://ret.cleanenergyregulator.gov.au.

[4] Y.V. Makarov, C. Loutan, J. Ma, and P. de Mello, "Operational impacts of wind generation on California power systems," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 1039-1050, May 2009.

[5] A. Arulampalam, M. Barnes, N. Jenkins, and J.B. Ekanayake, "Power quality and stability improvement of a wind farm using STATCOM supported with hybrid battery energy storage," *IEE Proc. Gen., Transmiss. Distrib.*, vol. 153, no. 6, pp. 701-710, Nov. 2006.

[6] J. Zeng, B. Zhang, C. Mao, and Y. Wang, "Use of battery energy storage system to improve the power quality and stability of wind farms," *in Proc. Int. Conf. Power Syst. Technol.*, 2006, pp. 1-6.

[7] K. Yoshimoto, T. Nanahara, and G. Koshimizu, "New control method for regulating state-of-charge of a battery in hybrid wind power/battery energy storage system," in *Proc. IEEE Power Syst. Conf. Expo.*, Oct. 29-Nov. 1, 2006, pp.1244-1251.

[8] S. Teleke, M.E. Baran, A.Q. Huang, S. Bhattacharya, and L. Anderson, "Control strategies for battery energy storage for wind farm dispatching," *IEEE Trans. Energy Convers.*, vol. 24, no. 3, pp. 725-732, Sep. 2009.

[9] S. Teleke, M.E. Baran, S. Bhattacharya, and A.Q. Huang, "Optimal control of battery energy storage for wind farm dispatching," *IEEE Trans. Energy Convers.*, vol. 25, no. 3, pp. 787-794, Sept. 2010.

[10] B. Hartmann and A. Dan, "Cooperation of a grid-connected wind farm and an energy storage unit---demonstration of a simulation tool," *IEEE Trans. Sustainab. Energy*, vol.3, no. 1, pp. 49-56, Jan. 2012.

[11] R.S. Garica and D. Weisser, "A wind-diesel system with hydrogen storage: Joint optimization of design and dispatch," *Renewable Energy*, vol. 31, no. 14, pp. 2296–2320, Nov. 2006.

[12] D.L. Yao, S.S. Choi, K.J. Tseng, and T.T. Lie, "A statistical approach to the design of a dispatchable wind power-battery energy storage system," *IEEE Trans. Energy Convers.*, vol. 24, no. 4, pp. 916-925, Dec. 2009.

[13] D.L. Yao, S.S. Choi, K.J. Tseng, and T.T. Lie, "Determination of short-term power dispatch schedule for a wind farm incorporated with dual-battery energy storage scheme," *IEEE Trans. Sustainab. Energy*, vol. 3, no. 1, pp. 74-84, Jan. 2012.

[14] Q. Li, S.S. Choi, Y. Yuan, and D.L. Yao, “On the determination of battery energy storage capacity and short-term power dispatch of a wind farm,” *IEEE Trans. Sustainab. Energy*, vol. 2, no. 2, pp. 148-158, Apr. 2011.

[15] G. Sideratos and N.D. Hatziargyriou, “An advanced statistical method for wind power forecasting,” *IEEE Trans. Power Syst.*, vol. 22, no. 1, pp. 258-265, Feb. 2007.

[16] K. Bhaskar and S.N. Singh “AWNN-assisted wind power forecasting using feed-forward neural network,” *IEEE Trans. Sustainab. Energy*, vol. 3, no. 2, pp. 306-315, Apr. 2012.

[17] The *OptiSeries* V1.0 User Manual, Hong Kong Polytechnic University, Sep. 2009.

[18] Mukund R.Patel. *Wind and Solar Power Systems, 1999 by CRC Press LLC.*

[19] H. Bludszuweit, J.A. Dominguez-Navarro, and A. Liombart, “Statistical Analysis of Wind Power Forecast Error,” *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 983-991, Aug. 2008.

[20] C. Luna, “Generation management using batteries in wind farms: economical and technical analysis for Spain,” *Energy Policy*, vol. 31, no. 1, pp. 126-139, Jan. 2009.

[21] Y. Zheng, Z.Y. Dong, F.J. Luo, K. Meng, J. Qiu, and K.P. Wong, “Optimal allocation of energy storage system for risk mitigation of DISCOs with high renewable penetrations,” *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 212-220, Jan. 2014.

[22] DOE Global Energy Storage Database, [Online]. Available: http://www.energystorageexchange.org.

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