A New Battery Approach to Wind Generation System in Frequency Control Market

Minh Y Nguyen*, Dinh Hung Nguyen* and Yong Tae Yoon†

Keywords: Battery energy storage, Wind power producer, Frequency control market, Battery management system

Wind power producers face many regulation costs in deregulated environment, which remarkably lowers the value of wind power in comparison with conventional sources. One of these costs is associated with the real-time variation of power output and being paid in frequency control market according to the variation band. This paper presents a new approach to coordination of battery energy storage in wind generation system for reducing the payment in frequency control market. The approach depends on the statistic data of wind generation and the prediction of frequency control market price to determine the optimal variation band which is then kept by the real-time charging and discharging of batteries, ultimately the minimum cost of frequency regulation can be obtained. The optimization problem is formulated as trade-off between the decrease in the regulation payment and the increase in the cost of using battery, and vice versa. The approach is applied to a study case and the results of simulation show its effectiveness.

1. Introduction

Electric power industry is experiencing a major restructuring process which intentionally pushes both generation and consumption sectors into market forces with the ultimate target of reducing the electric price. In this new market environment, wind power producers (WPPs) face many regulation costs due to the intermittence of natural resources (i.e. wind speed) and the accuracy limit of prediction tools (which is only about 10–15% even with a modern prediction tools). As a result, the competitiveness of WPPs is remarkably lowered in comparison with the conventional sources, e.g. gas-fired, coal-fired power plants.

A number of study efforts have been paid in order to increase the value of wind power in the deregulated market, most of them focus on the case of Denmark where the wind power shares about 20% of the total electricity demand (in 2007) [1]. In [2] and [3], an intraday (or after-sale) market with a smaller gate closure time (i.e. the time between market closure and physical delivery of electricity) is presented. In this approach, WPPs with better prediction accuracy can submit bids to correct the error of their bids in spot market (day-ahead). This eventually results in a smaller imbalance cost they need to pay. Some studies suggest an optimal bidding strategy for WPPs in spot market considering the probabilistic information of wind forecasting error as well as the asymmetry of regulation prices (up and down regulation) [4–8]. The outcome of these is that WPPs would intent to bid at a lower amount than the prediction to avoid the expensiveness of up regulation; by thus the entire imbalance cost can be reduced. Other works propose a cooperation of wind turbine-generator (WTG) and battery energy storage (BES) in a wind generation system (WGS) so that the synthesized power output can be controlled [10–12]. By this means, not only the imbalance cost can be mitigated (or even eliminated) but also WPPs can take arbitrage opportunity in spot market. This makes the idea of BES very attractive and promising.

The entire aforementioned researches are dealing with imbalance cost caused by the bidding error of WPPs in spot market. However, there is another regulation cost faced by WPPs in the deregulated market that accounts for the influence of the real-time variation of wind power output in system frequency, called frequency regulation (FR) cost. This cost is settled in frequency control market based on the width of output variation (i.e. variation band) and the frequency regulation price (FRP).

In this paper, we present a new approach of improving the value of wind power which focuses on decreasing the payment of WPPs in frequency control market. It is assumed that WPP is a price-taker in the market, i.e. no capability to alter the market price; and BES is incorporated in the WGS. The opportunity is that, WPP can estimate the FRP in the next day and depends on the probabilistic information of real-time variation of wind power output to determine the optimal variation bands. To get beyond the previous studies, the cost of BES is taken into consideration in this paper. Therefore, the problem is formulated as tradeoff between the expected decrease in FR cost and the expected increase in BES cost, and vice versa. The problem solution will detail the optimal variation bands that the power output should kept inside at each hour of the next day and based on which,

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the real-time charging/discharging strategy of BES would be decided.

The remainder of this paper is organized as follows. Section II presents the principle of frequency regulation in power system and the market for frequency control. Section III reviews the recently emerging studies of battery energy storage in renewable energy system and the proposal of battery management system (BMS). Section IV provides mathematical formulations and derivation for the optimality condition. The case study in Section V demonstrates the application of the proposed approach and the actual charging/discharging of BES, then shows its effectiveness compared to two other operation strategies. Finally, conclusive points are summarized in Section VI.

2. Principle of Frequency Regulation

There is a matter of fact that it is impossible to keep the system frequency always in the desired value (60Hz); instead power imbalance caused by the real-time variation of system users forces the system equilibrating with a frequency deviation [13]. In order to keep the system frequency remained in an acceptable limits, the well-known hierarchical control scheme has long been applied; which consists of three regulation levels: primary, secondary and tertiary regulation.

2.1 Hierarchical frequency control scheme

The primary regulation refers to the generation spontaneously provided by Generator-Turbine-Governor (G-T-G) units when the system frequency deviates from the desired value; it is called droop-characteristic or governor-free. This action is fast and usually stabilizing the system within 5–10 seconds. In power system, loads also respond to the change of frequency, however, there is high uncertainty associated with their actions; thus, generally, loads are not considered as sources of primary regulation [14]. It is noted that this regulation level does not fully compensate the power imbalance between supply and demand, but stabilize the system at a new equilibrium point with a small deviation of frequency:

$$\Delta f_s = \frac{\Delta P_s}{\beta_G + \beta_L} \tag{1}$$

where β_G and β_L are the sum of the droop-parameter (i.e. frequency-sensitivity) of all generators and loads in the system, [MW/Hz].

The secondary regulation refers to the generation provided by AGC set up on the technically qualified generating units, e.g. gas-fired generators [14]. This action is activated with the time constant (e.g. few minutes) to restore the system frequency to the desired value. It is worth noting that this regulation level is to compensate for the normal (slow and small) variation of loads (and nonconventional sources as well); thus it is also called load-following control. In the multi-area system, the AGC is determined based on the Area Control Error (ACE) signal which reflects the power imbalance within an area [17, 18]:

$$ACE_i = (\beta_G + \beta_L)_i \Delta f_s + \sum_{j=1}^{J} \Delta F_{ij} \tag{2}$$

where ACE_i is ACE signal for area i, [MW]; $(\beta_G + \beta_L)_i$ is the sum of the droop-parameters within area i, [MW/Hz]; and ΔF_{ij} is the power deviation from the scheduled value in the tie-line between area i and j, [MW]; J is the set of area connected to area i through tie-lines. Then, the AGC generation of generator Gn in area i is calculated according to its participation factor, G_{Gn}:

$$P_{Gn}^{agc} = G_{Gn} \cdot ACE_i \tag{3}$$

The participation factors of all AGC generators within a control area subject to a constraint that sum of them must be equal to one.

The tertiary regulation refers to the generation called when a large power imbalance occurs in the system, e.g. caused by unexpected change of loads or loss of important generating units. These unexpected disturbances may cause the system out of frequency limits, voltage limits, and/or transmission line capacity limits so that the reschedule of generating units and transmission lines in the system-wide is required. This action typically takes more than 10 minutes, and therefore, permits the wide participation of demand-side (load-shedding), spinning and non-spinning generators [14].

2.2 Frequency control market

In monopoly market, the task of maintaining the system frequency in acceptable limits is managed by System Operator (SO) and the cost of performing this regulation is passed to consumers in the price of electricity. In deregulated environment, however, it is important to relate cause and effect; or in other words, the rights and responsibilities of system users to the system performance (e.g. frequency) need to be cleared [13]. It is resulted in the frequency control market where loads (and non-conventional sources) pay and AGC generators get paid for the frequency regulation service they consume or provide, respectively. The Frequency Regulation Price (FRP) is determined in term of payment per capacity reversed for AGC of generators and payment per variation band of loads (and non-conventional sources), [$/MW].

The frequency regulation in deregulated environment can be traded either through pool or bilateral contracts [14, 15]. The power pool for frequency regulation in a specific area is managed by Independent System Operator (ISO) through a bidding mechanism. Bilateral contract, in difference, can be dealt between individual provider and consumer both within and across the boundaries of control area. Then, ACE signal is modified with a bit change:

$$ACE_i = (\beta_G + \beta_L)_i \Delta f_{sys} + \sum_{j=1}^{J} \Delta F_{ij} - \sum_{l=1}^{Bi} \Delta Pb_l \tag{4}$$

where Bi is the set of consumers within area i who have bilateral contract of frequency regulation; ΔPb_l is the power deviation of consumer l. The AGC generation by generator Gn is set as:

$$P_{Gn}^{agc} = G_{Gn} \cdot ACE_i + \sum_{m=1}^{M} \Delta Pb_{nm} \tag{5}$$

where G_{Gn} is the participation factor of generator Gn in frequency regulation pool; ΔPb_{nm} is the power deviation of consumer m who has bilateral contract of frequency regulation with generator Gn. M is the set of customers who have bilateral contract with generator Gn.

Therefore, once the FRP is cleared, the frequency regulation cost paid by loads and nonconventional sources (including wind power) can be calculated as follows:

$$C_k^{\mathrm{FR}} = \Delta P_k^{\pm} \cdot \lambda_k^{\mathrm{FR}} \tag{6}$$

where k is time index, e.g. hour index; C^{FR} is the frequency regulation cost, [$]; $\Delta P^{\pm}$ is the variation band, [MW]; and λ^{RT} is the frequency regulation price, [$/MW].

3. Battery Energy Storage System

Battery energy storage (BES) has long been a solution for improving the reliability and performance of power system; particularly, it is considered as the key element for integrating renewable sources in the electric network. Despite many advantages carried by BES, its application is very limited due to the lack of experience and tools for (i) operational cost optimization, and (ii) assessing the benefits considering market model [16]. This section reviews some emerging studies on BES which concern the operating condition, stress factor and lifetime model of battery in renewable application, and introduce a battery management system (BMS) for renewable energy system.

3.1 Operating condition, stress factor and lifetime model

Generally, the lifetime of a battery bank is given by manufacturer in term of Ah-throughput; that indicates the theoretical amount of Ah (ampere-hour) can be charged and discharged through the battery bank until the end-of-life is reached. This lifetime throughput is obtained by various test methods performing under certain conditions (i.e. standard condition). The matter of fact is that these conditions are usually not achievable in practice, particularly, under renewable application. Indeed, the operating condition of BES in renewable energy system is characterized by (i) partial state of charge (SoC), (ii) incomplete or rare full of charge, and (iii) wide range of ambient temperature [17]. In [18] and [19], six important stress factors are defined which link the operating condition to the lifetime of battery bank, such as charge factor, Ah-throughput, time between full charge, time at low SoC, and temperature. It is worth noting that these stress factors can physically increase the rate of one aging process and reduce the rate of another. For instance, a high temperature will accelerate the rate of corrosion, but will decrease the rate of formation of hard, irreversible sulphation products (in lead-acid battery) [20]. Therefore, quantifying the influence of stress factors on the lifetime of a whole battery bank needs a thorough understanding and analysis of the entire aging processes.

In order to evaluate the battery lifetime, three different approaches are presented in [18]–[20]. The first approach called performance-based model that is based on the simulation of each aging processes as functions of operating conditions and the change of performance values of the battery while the various aging processes take place. The battery is said to be end-of-life if the performance values across thresholds. This method is very accurate but may suffer from computation burden. The second approach, called Ah-throughput model that is based on an assumption that once a predetermined value of the Ah-throughput has been exceeded, the battery is considered to have reached end-of-life. For taking the operating condition into account, the weight factors are added; it is then called weighted Ah-throughput model. The third approach, called event-oriented model, is based on an assumption that the incremental loss of lifetime caused by different events is added up until a certain value is reached. Thus, in some sense, this approach shares the similar idea with the weighted Ah-throughput model.

3.2 Battery management system

In order to improve the lifetime and reliability of BES with respect to the application in renewable energy system, a battery management system (BMS) is proposed in [21]. This idea is to split battery bank of BES into several strings those are connected in parallel via switches. Each string can be controlled individually, by thus the standard condition are nearly obtained. The circuit concept of BMS is shown in Fig. 1.

In Fig. 1, the entire batteries of BES are divided into four parts (strings) which are connected in parallel via the main switches S_{M1}–S_{M4}. This provides the option of connecting or disconnecting the individual strings (B_1–B_4) independently from each other. By this means, some battery can be charged or discharged while the others do not have to be involved. In addition, the BMS comprises a DC/DC converter connected to DC bus through switches S_{C1}–S_{C4}. This component is to perform a full charge for each individual battery string when the available energy is not enough for full charge of entire batteries.

Therefore, during normal operation in renewable system BMS enables shorter cycles at low SoC, increase in the current rate and intensive full charge; those are major stress factors on the lifetime of battery.

4. Proposed Charging/discharging Scheme of BES

This section provides a mathematical formulation for determining the optimal variation band of WPP in response to the frequency regulation price (FRP) and the probabilistic information of real-time power output. The formulation is to minimize the total cost associated with frequency regulation which includes the payment in frequency control market and cost of BES. The formulation is restricted to the following assumptions:

1. WPP is a price-taker in the electric market, i.e. with no ability to alter the market clearing price.
2. The bidding in spot market is out of the scope of this paper, and without losing generality, the mean value ($\bar{P}$) is assumed to be bided.
3. The statistic information of the output variation in real-time is available, e.g. probability density function.
4. BMS is applied so that each battery string of BES is operating closely to the standard condition. Then, the theoretical lifetime throughput can be obtained.

4.1 Problem formulation

The problem is trading-off between the decrease in payment in frequency control market and the increase in expense of BES, and vice versus. The total cost associated with frequency regulation of WPP is calculated as follows:

$$C[k] = \lambda_k^{FR} \cdot \Delta P_k^{\pm} + C_B[k] \tag{7}$$

where λ_k^{FR} is the FRP at hour k, [\$/MW]; $\Delta P_k^{\pm}$ is variation band at hour k; and $C_B[k]$ is the BES cost at hour k, [\$]. From the assumption 4, it is implied that the theoretical lifetime throughput can be achieved; therefore it is able to evaluate the cost associated with per MWh charged and discharged through BES, called battery wear cost [29], as follows:

$$c^{bw} = \frac{C_{rep}}{NQ_{lifetime}\sqrt{\eta_{rt}}} \tag{8}$$

The BES cost in k-th hour can be approximately calculated as follows:

$$C_B[k] = c^{bw}\frac{1}{2}\left(\eta_{rt}\int_k p_{ch}\,dt + \int_k p_{dis}\,dt\right) \tag{9}$$

In (9), the amount of energy charged and discharged through BES is approximated as the mean of charging and discharging amounts. This approximation is valid because the cumulative charging and discharging energies will converge as the operation time increases. The problem then become determining the optimal variation band at each hour that gives the minimum overall cost:

$$\min_{\Delta P_k^{\pm}} \mathop{\mathrm{E}}_{P_w(t)} \left\{ \lambda_k^{FR}\Delta P_k^{\pm} + \frac{1}{2}c^{bw}\left(\eta_{rt}\int_k p_{ch}\,dt + \int_k p_{dis}\,dt\right) \right\} \tag{10}$$

4.2 Solution derivation

Before deriving solution, it is needed to define the operating strategy of BES to handle the terms of charging and discharging power in (10). That is, assuming the optimal variation band has been determined; the BES is responsible of keeping the output of WPP inside that band. And for not over-use BES (i.e. increase in BES cost), the charging and discharging strategy are to adjust the output lying in the boundaries of the optimal variation band when it comes out, otherwise BES does not response. In mathematical expressions,

$$p_{ch} = \begin{cases} p_w(t) - \Delta P_k^{\pm} & \text{if} \quad p_w(t) \ge \Delta P_k^{\pm} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

and,

$$p_{dis} = \begin{cases} -\left(p_w(t) + \Delta P_k^{\pm}\right) & \text{if} \quad p_w(t) \le -\Delta P_k^{\pm} \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

where $p_w(t)$ is the real-time variation from the mean value of output, [MW].

Take the expectation of (10) gives:

$$\min_{\Delta P_k^{\pm}} \quad \bar{\lambda}_k^{FR} \Delta P_k^{\pm} + c^{bw} \frac{1}{2} \left(\eta_{rt} \int \underset{k p_w(t)}{\mathrm{E}} \{p_{ch}\} dt + \int \underset{k p_w(t)}{\mathrm{E}} \{p_{dis}\} dt \right) \tag{13}$$

The "bar" on the FRP in (13) represents the mean of prediction.

According to assumption 3, the probability density function of output is known in form of normal (Gaussian) distribution:

$$\mathrm{f}(p_w) = \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left(-\frac{(p_w)^2}{2\sigma^2} \right) \tag{14}$$

where σ is the standard deviation, [MW]. It is further assumed that the real-time variation has zero mean; or in other words, there is no bias in the prediction of hourly generation. From (11) and (12), the energy charged to and discharged from BES can be calculated as Fig. 3:

$$\begin{aligned} \int \underset{k p_w(t)}{\mathrm{E}} \{p_{ch}\} dt &= \int \underset{k p_w(t)}{\mathrm{E}} \{p_{dis}\} dt \\ &= \int_{\Delta P_k^{\pm}}^{\infty} \mathrm{f}(p_w)(p_w - \Delta P_k^{\pm}) dp_w \end{aligned} \tag{15}$$

Substituting (15) into (13), the problem becomes:

$$\min_{\Delta P_k^{\pm}} \quad \bar{\lambda}_k^{FR} \Delta P_k^{\pm} + \frac{1}{2} c^{bw} (1 + \eta_{rt}) \left(\int_{\Delta P_k^{\pm}}^{\infty} \mathrm{f}(p_w)(p_w - \Delta P_k^{\pm}) dp_w \right) \tag{16}$$

Take derivation of (16) with respect to variation band ($\Delta P^{\pm}$) and use mathematically equivalent transformation, we obtain the optimality condition for the optimal variation band as follows:

$$\bar{\lambda}_k^{FR} - \frac{1}{2} c^{bw} (1 + \eta_{rt}) \left(1 - \mathrm{F}(\Delta P_k^{\pm})\right) = 0 \tag{17}$$

or when the probability density function in (14) is applied:

$$\bar{\lambda}_k^{FR} - \frac{1}{2} c^{bw} (1 + \eta_{rt}) \left(1 - \int_{-\infty}^{\Delta P_k^{\pm}} \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left(-\frac{(p_w)^2}{2\sigma^2} \right) dp_w \right) = 0 \tag{18}$$

where $\mathrm{F}(p_w)$ is the cumulative probability function of real-time output, [0, 1].

Eqs. (17) and (18) show the relationship between the predicted FRP, battery wear cost, real-time variation (represented in term of probabilistic function) and the optimal variation band. Analyzing (17) and (18), it can be seen that the increase in λ^{FR} will results in the decrease in $\Delta P^{\pm}$, and vice versus. Likewise, the increase in c^{bw} also results in the increase in $\Delta P^{\pm}$, and vice versus. That is logically true because in either case when the FRP is high or battery wear cost is low, WPP intends to use BES more, i.e. smaller variation band, to avoid the expensiveness of FRP or take advantage of low BES cost. Otherwise, when FRP is low or battery wear cost is high, WPP will use BES less, accompanied by large variation band, to benefit from low market price and avoid high cost of BES.

5. Case Study

5.1 Determination of optimal variable band

In this section, we consider the case of WPP owning 10 MW wind power and 1 MWh BES Fig. 2. Assuming that there is no bias in wind power prediction and the mean values are bided in the spot market. The statistic data shows that the real-time variation of wind power output follows the Gaussian distribution rule which has zero mean and the standard deviation of 10 percents of the mean of prediction. The BES utilizes battery type Surrette 4KS25P manufactured by Surrette Battery Company [31]. The 4KS25P has: C_{rep} = \$1,000/unit; $Q_{lifetime}$ = 10,494kWh; η_{rt} = 0.8, then the battery wear cost of BES can be calculated by (8): c^{bw} = \$106.5/MWh. Once the prediction of FRP and wind generation in the next day is available, the optimal variation bands for each hour of the next day can be obtained from (17) or (18). The results are presented in Table 1.

In order to observe the response of the optimal variation bands ($\Delta P^{\pm}$) to the change of FRP (λ^{FT}) and the output variation (p_w), their normalized representations are displayed in Fig. 4.

It can be seen that the optimal variation band (square-marked) seems to vary proportionally to the standard deviation of prediction (circle-marked) and inversely to the frequency regulation price (triangle-marked). That is logically true because when the power prediction is high, meaning the real-time deviation of power output will be large, the WPP should regulate BES with a large variation band to avoid the over-use of BES. This can be illustrated by the results at hour 4 and 5: the FRPs are near equal but the difference in power prediction will result in the difference of optimal variation band. On the other hand, when the FRP is low, the WPP should take advantage of cheap market price which results in large variation band as well. Comparing the results in hour 1 and 13, the power predictions are nearly the same but the higher FRP will result in lower optimal variation band.

5.2 Real-time simulation

In this section, the real-time charging/discharging operation of BES in response to the optimal variation bands is simulated. The real-time variation of wind power output and the optimal variation band are presented in Fig. 5. The BES will be controlled to charge or discharge when the output exceeds the pre-determined optimal bands. Fig. 6 shows the charging/discharging power and SoC of BES during the day.

It can be seen that even the cumulative amount of charge and discharge are equal statistically, the SoC of BES gradually decreases during the day. That is because of the energy losses in charging and discharging through BES. Fortunately, this problem can be easily handled by trading in spot market (that is out of this paper scope). It is worth noting that the BES is only used when the output exceeds the optimal variation bands, i.e. with a relatively low probability density function. Therefore, only small volume of BES (1 MWh) is enough for handling the problem, i.e. keeping the synthesized output inside the optimal bands Fig. 6.

The effectiveness of the proposed approach is illustrated by comparing to two other operating strategies: (i) without using BES, and (ii) intensively use of BES. The first strategy does not consider BES so that WPP must pay for the entire variation bands according to the FRP. The second strategy, on the other hand, uses BES intensively to fully compensate for the real-time variation; that means WPP does not have to pay any in frequency control market. However, both strategies result in a much higher cost compared to the proposed scheme Table 2.

6. Conclusion

This paper presents a new approach of BES for improving the value of wind power in deregulated market. The approach deals with the cost associated with frequency regulation faced by WPP in power system, rather than the imbalance cost as in the previous studies. Then the paper provides a framework for determining the optimal variation band to which BES should be control to maintain the power output inside. The case study shows that the proposed scheme can significantly reduce the frequency regulation cost of WPP either compared to the cases without using BES and intensive use of BES.

It is noted that the physical constraints of BES such as minimum SoC, maximum rate of charge/discharge, etc. are handled in designing the battery controller which is out of the scope of this paper. In addition, the bidding strategy in spot market is also not considered that needs to take care of the gradually decrease of the SoC of BES as the above discussion. For instance, the WPP should bid somehow smaller than the mean value to compensate for the energy losses in charging and discharging of BES.

Glossary

k	time index, [hour]
Gn	n-th generator
Δf_s	system frequency deviation, [Hz]
ΔP_s	system power imbalance, [MW]
β	droop-parameter, [MW/Hz]
ACE	area control error signal, [MW]
G	AGC participation factor
P^{agc}	AGC power generation, [MW]
ΔF	power deviation in tie-line between areas, [MW]
ΔPb	power deviation of bilateral contract customer, [MW]
λ^{FR}	frequency regulation price, [$/MW]
C^{FR}	frequency regulation cost, [$]
C_B	battery utilization cost, [$]
c^{bw}	battery wear cost, [$/MWh]
C_{rep}	battery replacement cost, [$]
η_{rt}	battery round-trip efficiency
N	number of batteries in a bank
$Q_{lifetime}$	battery lifetime throughput, [MWh]
$\Delta P^{\pm}$	variation band, [MW]
p_{ch}	BES charging power, [MW]
p_{dis}	BES discharging power, [MW]
p_w	real-time deviation of wind power output, [MW]
$\bar{P}$	prediction of (hourly) power generation, [MW]
p_{out}	synthesized power output deviation, [MW]

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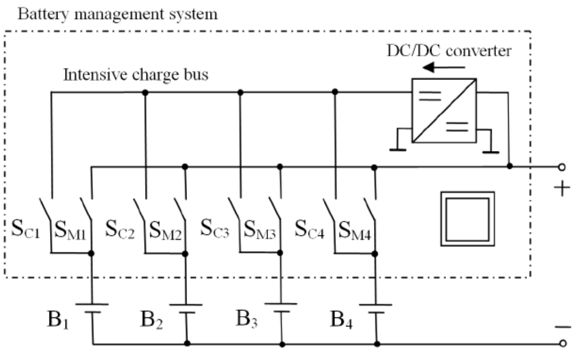

Fig. 1. Circuit concept of BMS with four parallel switched battery strings (B1–B4).

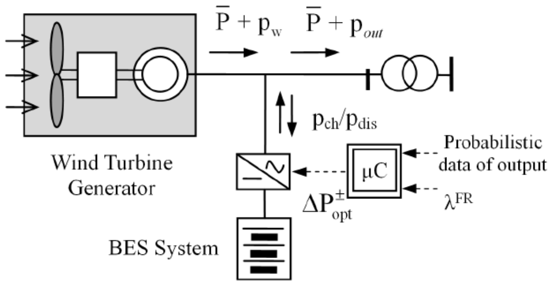

Fig. 2. Outline of WGS with BES

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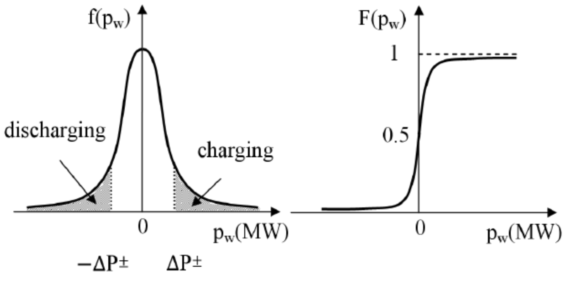

Fig. 3. Probability density function and cumulative probability function of real-time variation

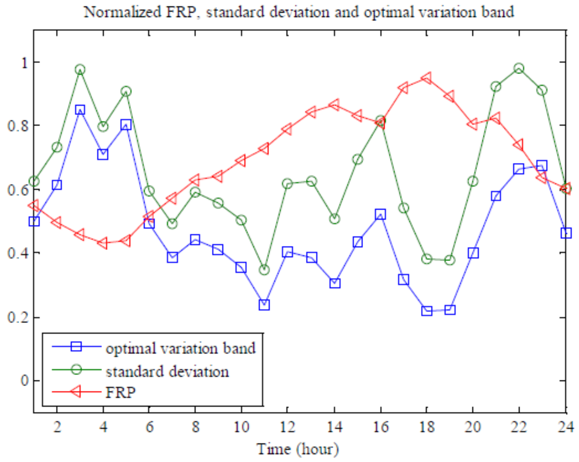

Fig. 4. Normalized standard deviation, [1MW]; FRP, [$20/MW]; and the optimal variation bands, [1.5MW] at each hour of the day

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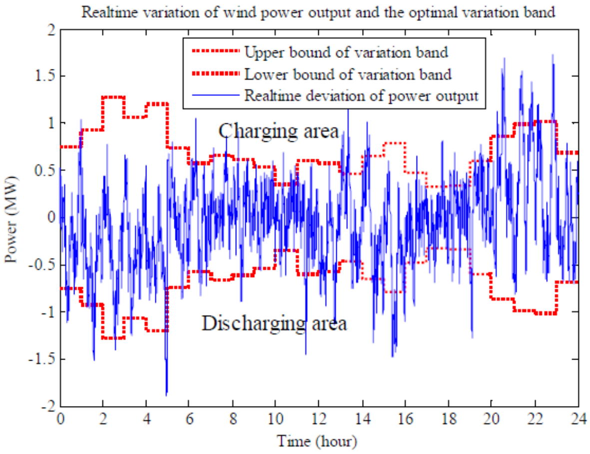

Fig. 5. Real-time variation of wind power output and the optimal variation band during the day

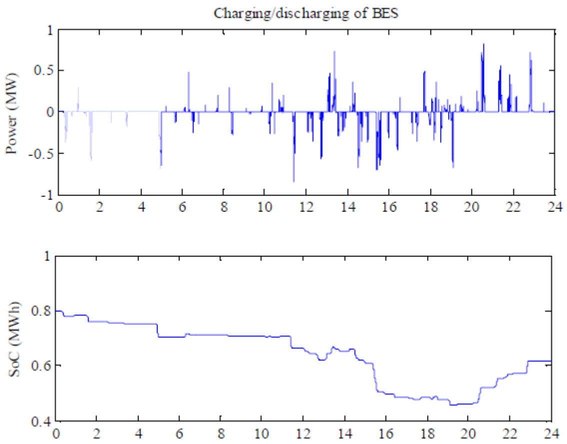

Fig. 6. Charging/discharging power and SoC of BES during the day

Time (hour)	$\bar{P}$ (MW)	λ^{FR} ($/MW)	$\Delta P^{\pm}$ (MW)	Time (hour)	$\bar{P}$ (MW)	λ^{FR} ($/MW)	$\Delta P^{\pm}$ (MW)
1	16.240	10.96	0.7505	13	6.242	16.88	0.5801
2	7.307	9.89	0.9228	14	5.058	17.34	0.4608
3	9.765	9.13	1.7729	15	6.937	16.66	0.6510
4	7.957	8.66	1.0644	16	8.167	16.14	0.7840
5	9.082	8.81	1.2064	17	5.432	18.35	0.4736
6	5.950	10.33	0.7362	18	3.835	18.98	0.3250
7	4.928	11.43	0.5803	19	3.765	17.84	0.3355
8	5.924	12.62	0.6622	20	6.242	16.07	0.6010
9	5.590	12.81	0.6196	21	9.214	16.49	0.8713
10	5.041	13.81	0.5349	22	9.794	14.80	0.9963
11	3.458	14.58	0.3548	23	9.120	12.71	1.0156
12	6.198	15.77	0.6044	24	6.024	12.05	0.6903

Table 1. The prediction of wind generation, FR price and optimal variable bands

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Operation strategies	BES cost [$]	FR cost [$]	Total [$]
Without using BES	0	341.12	341.12
Intensive use of BES	416.40	0	416.40
Proposed scheme	33.37	223.65	257.02

Table 2. Comparison of different operation strategies

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