Rolling Optimization of Wind Farm and Energy Storage System in Electricity Markets

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***Abstract*—Intraday energy markets have been established in some power markets mainly because of large-scale wind power integration. Inspired by the Spanish power market, this paper proposes a modified market design which contains day-ahead and intraday energy bidding sections to better accommodate stochastic wind energy. Then coordinated operation of the wind farm (WF) and energy storage system (ESS) is studied. Rolling stochastic optimization formulations for day-ahead, intraday biddings and real-time operations are put forward to obtain the optimal bidding strategy of WF-ESS union in each bidding section to maximize its overall profit. Case studies and sensitivity analyses are carried out on a union of WFs and a pumped storage plant (PSP). Simulation results show that the proposed rolling optimization method can effectively utilize the updated wind power forecast data and regulation capability of ESS, and thus increase profit for the union prominently.**

***Index Terms*—Energy storage system, intraday bidding, pumped storage plant, rolling optimization, wind farm.**

NOMENCLATURE

Index Sets:

$I=\{1,2\ldots s\}$	Set of day-ahead wind power forecast scenarios.
$H=\{1,2\ldots 24\}$	Set of 1-h periods in the future 12–36 h.
$K=\{1,2\ldots 24\}$	Set of 10-min intervals in the future 4–8 h.
$J=\{1,2\ldots 20\}$	Set of 1-h periods in the future 8–28 h.
$M=\{1,2\ldots 10\}$	Set of 1-min intervals in the future 1–10 min.

Functions:

$\mathrm{Pr}(\cdot)$	Probability of a given event
$\mathrm{Ex}(\cdot)$	Expectation of the stochastic variable.
$S_t^K(\cdot)$	Profit in interval t of set K.
$S_t^J(\cdot)$	Profit in interval t of set J.
$\xi_t(\cdot)$	Random wind power output at the given forecast wind speed.
$F(\cdot)$	Fluctuation of a sequential data.

Variables:

p_t^{da}, p_t^{ha}	Day-ahead/intraday power bidding for interval t.
$p_{t,i}^{w}$	Power generation of wind farm (WF) in interval t, scenario i.
$p_{t,i}^{p}, p_{t,i}^{g}$	Pumping/generating power of pumped storage plant (PSP) at interval t, scenario i.
$s_{t,i}^{p}, s_{t,i}^{g}$	On/off state of pumping/generating at interval t, scenarios i.
n_t^p	Number of running pumping turbines at interval t.
n_t^{su}, n_t^{sd}	Number of start-up/shutdown pumping turbines at the end of interval t.
$E_{t,i}$	Residue energy of PSP at interval t, scenario i.
ω_t^p	Weighting factor of profit in objective function of interval t.
ω^E	Weighting factor of residue energy deviation in objective function of interval t.
$\Delta p_t^+, \Delta p_t^-$	Deviation between actual output and intraday bidding of interval t.
$\Delta p_t^{\mathrm{bid}}$	Deviation between day-ahead and intraday bidding of interval t.
$p_{t,a}^{\mathrm{union}}, p_{t,\mathrm{ins}}^{\mathrm{union}}$	Actual power/output instruction of WF-PSP union at interval t.

Constants:

ρ_i	Weighting factor of wind power scenario i in the day-ahead optimization.
Δt_m	Duration of an interval in index set K.
Δt_h	Duration of an interval in index set J, H.
π_t	Electricity price of interval t.
$E_{\min}, E_{\max}$	Lower/upper bound of residue energy of PSP.
α	Confidence level of chance constraint.
$p_{t,i}^{wf}$	Wind power forecast of interval t, scenario i.
C_{su}, C_{sd}	Startup/shutdown cost of pumping unit per event.
γ^+, γ^-	Penalty factor of electricity price for positive/negative deviation between actual output and bidding of interval t.
β	Penalty factor of electricity price for the deviation between day-ahead and intraday bidding of interval t.
B_f^1, B_f^{10}	Ramping limit on wind power output for every 1 min and 10 min.

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N	Total number of pumping/generating turbines.
N_{ud}	Upper limit of start-up and shutdown times per day of pumping turbines.
$p_{\min}, p_{\max}$	Minimal/maximal pumping power of each unit.
$g_{\min}, g_{\max}$	Minimal/maximal generating power of each unit.
η_c, η_d	Energy efficiency of pumping/generating process.

I. Introduction

WIND power capacity has increased dramatically all around the world in recent years. However, a lot of new problems came up for power system operation and planning because of the intermittent and uncertain nature of wind power. As wind power generation depends on the chaotic weather system [1], its relative forecast error is quite large comparing to that of power system load. Consequently, operators of wind farms (WFs) face high risks bidding into competitive power market.

There are usually two main means to mitigate the risks. The first one is that a WF cooperates with an energy storage system (ESS) to take part in a power market jointly. Among varieties of ESSs, pumped storage plant (PSP) has the most mature technology and the largest capacity with relatively low per unit investment cost. Numerous studies have been focusing on the coordination of PSP and WF. In [2], the authors propose a new mode for WF and PSP coordination. Deterministic and stochastic optimization models are built to solve the day-ahead operational planning problem. Reference [3] formulates a two-stage stochastic optimization model to maximize the profit of a WF-PSP union under the Spanish power market environment. The advantage of joint operation over individual bidding into the market is further analyzed. References [4] and [5] discuss the benefits of investment and peak-shaving effect that WF-PSP union can bring.

On the other hand, wind power forecast errors increase with the extension of the forecast time horizon, which means the forecast results become more accurate when it comes closer to the real-time [6], [7]. Consequently, the second way to reduce the risks of WF biddings is rolling dispatch/operation, which has been presented by some researchers. Reference [8] proposes a rolling unit commitment methodology and exams potential cost savings by committing units on the system more frequently. In some market designs, WFs can revise their biddings to mitigate the deviation penalty brought by the day-ahead forecast errors, and the system operator (SO) can reduce reserve capacity for the system [9], [10]. So intraday rebidding is beneficial to both WFs and system operation [11], [12].

Although there are quite a lot of researches studying these two aspects separately, few of them have considered the optimal operation of the WF and ESS in a market that allows for rolling energy bidding. In fact, the Spanish power market as well as the Nordic one has an intraday energy rebidding section. It is organized six times a day and biddings can be submitted about 4 h in advance, covering upcoming 24 h [13]. However, wind power forecast error increases distinctly with time horizon, so the intraday forecast power of longer horizon is no more credible than the corresponding day-ahead value. Besides, the intraday market opens six times a day. WFs need to revise their output plan repeatedly, but only the biddings for *near future* (for example, 4–8 h) can become effective.

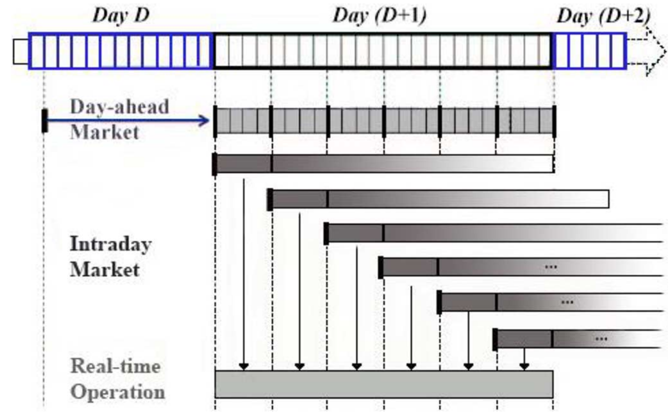

Fig. 1. Time frame of electricity market.

Based on the mechanism of the Spanish power market, this paper proposes a modified market design that allows for day-ahead and intraday bidding. Then a sequential series of stochastic optimization formulations are put forward to maximize the joint profit of WF and PSP in each section of the market. This paper is organized as follows. Section II introduces the proposed day-ahead and intraday bidding rules, as well as settlement and penalty rules. Rolling optimization models are formulated in Section III, where data flow between these models together with the way of depicting wind power forecast errors is illustrated. Section IV gives details of the application cases, discusses the results and makes sensitivity analyses. In the end, conclusions are demonstrated in Section V.

II. Time Frame for Revised Electricity Market

In order to better accommodate the day-ahead and intraday combined strategy, a three-stage electricity market design is proposed based on the Spanish power market. As depicted in Fig. 1, day-ahead biddings cover the 24 h of day $(D+1)$ [14]. In each intraday energy rebidding section participants optimize for following 24 h, but only submit the biddings of the next 4 h to the system operator. In real-time operation, participants try to follow their biddings, and get a settlement as well as the penalty according to their actual output.

A. Day-Ahead Bidding Rules

Day-ahead market begins at 12:00 every day. Power producers give their biddings to the market with 12–36 h in advance [13]. Take the WF-PSP union for example, it needs to submit bids $\{p_t^{da}\}$ for each of the 24 h of the next day, as illustrated in [3].

B. Intraday Bidding Rules

In order to better utilize the updated wind power forecast, a set of modified intraday bidding rules are proposed based on the Spanish market design:

1) In the intraday market, participants can submit their biddings every 4 h. Namely the intraday market opens at 0:00, 4:00, 8:00, 12:00, 16:00, and 20:00.

TABLE I
STANDARD FOR WIND POWER RAMPING LIMIT

Capacity (MW)	Limit of active power change in 10 min (MW)	Limit of active power change in 1 min (MW)
<30	10	3
30-150	Capacity/3	Capacity/10
>150	50	15

2) In the intraday bidding section, participants can revise their generation plan for the future 4 to 8 h, at the time resolution of 10 min. The deviation between intraday and day-ahead biddings will be penalized.
3) The submitted generation plan cannot be revised anymore and participants would be penalized if a deviation occurred in the real-time operation.

C. Real-Time Operation

In the real-time operation, generators will be penalized if there is deviation between the intraday biddings and average power output of every 10 min. Besides, the fluctuation of output should be constrained according to corresponding technical standards. For example, in China, the allowable power change in 1 min and 10 min is determined by the size of the WF, as is shown in Table I. In Germany the fluctuation in 1 min should be below 10% of the WF capacity [15].

SCADA systems of most WFs usually record data every minute. So the value of active power change in 1 min $\Delta p_{k,1}$ is obvious, as shown in (1). However, the definition of power change in 10 min is ambiguous. In this paper, two definitions $\Delta p^{\mathrm{I}}_{k,10}$ and $\Delta p^{\mathrm{II}}_{k,10}$ are used by (2) and (3):

$$\Delta p_{k,1} = |p_{k+1} - p_k| \tag{1}$$
$$\Delta p^{\mathrm{I}}_{k,10} = |P_{k+10} - P_k| \tag{2}$$
$$\Delta p^{\mathrm{II}}_{k,10} = \max\{(P_i - P_j)|i, j = k, k+1 \ldots k+9\}. \tag{3}$$

More specifically, at 12:00 of Day D, the day-ahead market opens and the WF-PSP union can bid its generation plan for 0:00–24:00 of Day $(D+1)$. It can also bid generation plan for future 4–8 h, i.e., 16:00–20:00. At 16:00, the intraday market opens again and the union can bid its generation plan for 20:00–24:00. The same process occurs every 4 h. With time approaching, the revenues and penalties are settled every 10 min according to average power in the 10 min and intraday biddings.

III. ROLLING OPTIMIZATION FRAMEWORK

A. Data Flow of Sections

Operation decisions of WF-PSP union in one section of market couple with those of other sections, and they together affect the total profit. Fig. 2 illustrates the data flow between different optimizations. Taking wind power forecast for future 12–36 h and initial residue energy forecast as input, the WF-PSP union can submit the day-ahead biddings based on the day-ahead optimization model. After the day-ahead market clearing is completed, the results, including cleared electricity quantities and prices, are passed to intraday optimization,

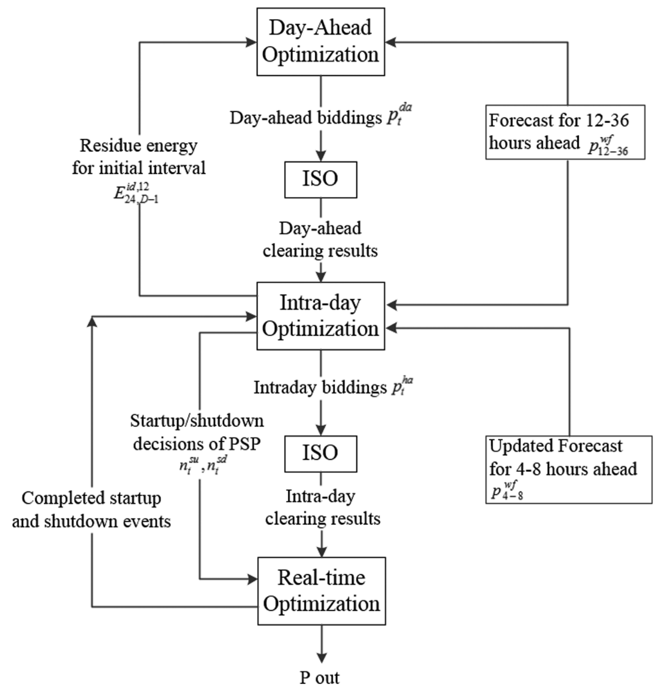

Fig. 2. Diagram of data flow between each market section.

whose output, such as startup/shutdown decisions and intraday biddings are used to calculate expected profit. In the following discussions of this paper, it is assumed that the WF-PSP union is a price taker and all its biddings are accepted by the electricity market. The real-time optimization makes the final output decisions based on the cleared intraday biddings and startup/shutdown decisions, and the actual profit can be computed. The completed startup and shutdown events are counted and considered in the following intraday optimizations.

B. Initial Residue Energy of Different Optimizations

The most notable difference between PSP and thermal generators is that the limited volume of the reservoir makes output/input power of different time intervals coupled with each other. In this case, the initial energy of PSP is essential in the optimization model. This is because if the actual initial energy of PSP deviated much from what was set in the optimization model, the energy in following time intervals may violate the allowable ranges according to the operational schedule. In this paper, the initial energy of PSP used for the rolling optimization is determined and adjusted as following:

1) In day-ahead optimization, the initial residue energy value of day D, $E^{da}_{0,D}$ is determined by the intraday optimization conducted at 12:00 and is equal to the optimal value at 24:00 day $(D-1)$, $E^{id,12}_{24,D-1}$.
2) The kth intraday optimization begins at the $(4k-4)$th hour. The initial residue energy value $E^{id,4k-4}_{4k,D}$ is determined by the result of $(k-1)$th optimization. More specifically, the value $E^{id,4k-4}_{4k,D}$ is equal to the sum of $(k-1)$th intraday optimization result $E^{id,4k-8}_{4k,D}$ and the latest adjustment δ. δ is the deviation of real residue energy and initial residue energy of $(k-1)$th intraday optimization $\delta = E_{4k-4,D} - E^{id,4k-8}_{4k-4,D}$, $E^{id,4k-4}_{4k,D} = E_{4k-4,D} - E^{id,4k-8}_{4k-4,D} + E^{id,4k-8}_{4k,D}$.

3) In real-time optimal control, the initial residue energy of the current control period is just the present measurement value.

C. Optimization Model of Each Market

1) Day-Ahead Market: In the day-ahead market, variables including $\{p_t^{da}, p_{h,i}^w, p_{h,i}^g, p_{h,i}^p, n_{h,i}^{su}, n_{h,i}^{sd}\}$ will be solved in optimization but only the day-ahead biddings $\{p_t^{da}\}$ will be passed to the intraday optimization. The day-ahead optimization model is a two-stage model. The day-ahead biddings are *here-and-now solutions* which make the expected profit maximal and the other intermediate ones are *wait-and-see* solutions. The uncertainty of wind power is presented as multiple scenarios which are obtained based on forecast results:

$$\text{Max}\sum_{i\in I}\left[\rho_i\sum_{h\in H}\begin{pmatrix}\pi_h\left(p_{h,i}^w+p_{h,i}^g-p_{h,i}^p\right)\Delta t_h\\ -\left(C_{su}n_{h,i}^{su}+C_{sd}n_{h,i}^{sd}\right)\\ -\gamma^+\pi_h\Delta p_{h,i}^+\Delta t_h-\gamma^-\pi_h\Delta p_{h,i}^-\Delta t_h\end{pmatrix}\right] \tag{4}$$

$$\text{s.t.}\quad 0\le p_{h,i}^w\le p_{h,i}^{wf}\quad h\in H, i\in I \tag{5}$$

$$\Delta p_{h,i}^+=\text{Max}\left(0,p_{h,i}^w+p_{h,i}^g-p_{h,i}^p-p_h^{da}\right)\quad h\in H, i\in I \tag{6}$$

$$\Delta p_{h,i}^-=-\text{Min}\left(0,p_{h,i}^w+p_{h,i}^g-p_{h,i}^p-p_h^{da}\right)\quad h\in H, i\in I \tag{7}$$

$$s_{h,i}^p+s_{h,i}^g\le 1\quad s_{h,i}^p, s_{h,i}^g\in\{0,1\},\ h\in H, i\in I \tag{8}$$

$$s_{h,i}^p\le n_{h,i}^p\le s_{h,i}^pN\quad h\in H, i\in I \tag{9}$$

$$n_{h+1,i}^p=n_{h,i}^p+n_{h,i}^{su}-n_{h,i}^{sd}\quad h\in H, i\in I \tag{10}$$

$$p_{\min}n_{h,i}^p\le p_{h,i}^p\le p_{\max}n_{h,i}^p\quad h\in H, i\in I \tag{11}$$

$$s_{h,i}^g g_{\min}\le p_{h,i}^g\le s_{h,i}^g g_{\max}N\quad h\in H, i\in I \tag{12}$$

$$\sum_{k=1}^{24}\left(n_{h,i}^{su}+n_{h,i}^{sd}\right)\le N_{ud}\quad h\in H, i\in I \tag{13}$$

$$E_{h+1,i}=E_{h,i}+p_{h,i}^p\Delta t_h\eta_c-p_{h,i}^g\Delta t_h/\eta_d\quad h\in H, i\in I \tag{14}$$

$$E_{\min}\le E_{h,i}\le E_{\max}\quad h\in H, i\in I. \tag{15}$$

Equation (4) considers the revenue of generation, cost of startup and shutdown, and the penalty for deviation. Equation (5) limits the output range of the WF. Positive and negative deviation is defined in (6) and (7). Equation (8) prohibits the simultaneous charging (pumping) and discharging (generating). On/off states and running number is restricted by (9)–(13). Equation (14)–(15) reveals the upper and lower bound of reserve volume.

2) Intraday Market: Although WF-ESS unions only need to bid for the future 4–8 h every time the intraday market opens, they still need to consider the effect of future hours' wind power because the residue energy of PSP is coupled with the *farther future*. On the other hand, as the wind power forecast error increases distinctly with time, the *near* and *farther future* decision should be set with different weights. Consequently, we define the objective function and constraints of these two parts separately. For the *near future*, as the forecast errors are relatively small, chance constraint is applied. For the *farther future*, scenarios are generated to represent the stochastic nature of wind power as the chance constraints for the large forecast error case would narrow feasible region, which would reduce the expected profit [16].

The detailed formulation is described as follows:

$$\text{Max}\quad S \tag{16}$$

$$\text{s.t.}\quad S=\sum_{t\in K}S_t^K+\sum_{t\in J}\omega_t^pS_t^J \tag{17}$$

$$\begin{aligned}S_t^K&=\pi_t\left(p_t^w+p_t^g-p_t^p\right)\Delta t_m\\&\quad-\left(C_{su}n_t^{su}+C_{sd}n_t^{sd}\right)-\beta\pi_t\Delta p_t^{\text{bid}}\Delta t_m\quad t\in K\end{aligned} \tag{18}$$

$$\begin{aligned}S_t^J&=\text{Ex}\left\{\begin{matrix}\pi_t\left(p_{t,i}^w+p_{t,i}^g-p_{t,i}^p\right)\Delta t_h\\ -\pi_t(\gamma^+\Delta p_{t,i}^++\gamma^-\Delta p_{t,i}^-)\Delta t_h\end{matrix}\right\}\\&\quad-\left(C_{su}n_t^{su}+C_{sd}n_t^{sd}\right)-\beta\pi_t\Delta p_t^{\text{bid}}\Delta t_h\\&\qquad t\in J, i\in I\end{aligned} \tag{19}$$

$$p_t^w+p_t^g-p_t^p=P_t^{ha}\quad t\in K \tag{20}$$

$$\Pr\left\{0\le p_t^w\le p_t^{wf}+\xi_t(v_t)\right\}>\alpha\quad t\in K \tag{21}$$

$$-\Delta p_t^{\text{bid}}\le P_t^{ha}-p_t^{da}\le\Delta p_t^{\text{bid}}\quad t\in K,J \tag{22}$$

$$-\Delta p_{t,i}^-\le p_{t,i}^w+p_{t,i}^g-p_{t,i}^p-p_t^{ha}\le\Delta p_t^+\quad t\in J, i\in I \tag{23}$$

$$\left|p_t^{ha}-p_{t-1}^{ha}\right|\le B_f^{10}\quad t\in K \tag{24}$$

$$s_t^p+s_t^g\le 1\quad s_t^p, s_t^g\in\{0,1\}\quad t\in K,J \tag{25}$$

$$s_t^p\le n_t^p\le s_t^pN\quad t\in K,J \tag{26}$$

$$n_{t+1}^p=n_t^p+n_t^{su}-n_t^{sd}\quad t\in K,J \tag{27}$$

$$\sum_{t\in K,J}\left(n_t^{su}+n_t^{sd}\right)<N_{ud} \tag{28}$$

$$p_{\min}n_t^p\le p_t^p\le p_{\max}n_t^p\quad t\in K \tag{29}$$

$$p_{\min}n_{t,i}^p\le p_{t,i}^p\le p_{\max}n_{t,i}^p\quad t\in J, i\in I \tag{30}$$

$$s_t^g g_{\min}\le p_t^g\le s_t^g g_{\max}N\quad t\in K \tag{31}$$

$$s_{t,i}^g g_{\min}\le p_{t,i}^g\le s_{t,i}^g g_{\max}N\quad t\in J, i\in I \tag{32}$$

$$E_{t+1}=E_t+p_t^p\Delta t_h\eta_c-p_t^g\Delta t_h/\eta_d\quad t\in K \tag{33}$$

$$E_{t+1,i}=E_{t,i}+p_{t,i}^p\Delta t_h\eta_c-p_{t,i}^g\Delta t_h/\eta_d\quad t\in J, i\in I \tag{34}$$

$$E_{\min}\le E_t\le E_{\max}\quad t\in K \tag{35}$$

$$E_{\min}\le E_{t,i}\le E_{\max}\quad t\in J, i\in I. \tag{36}$$

Equations (16) and (17) define the objective to maximize the profit S of WF-PSP union. As the target power for *farther future* need not be submitted and the forecast power is not as credible as that of the *near future*, the S_t^J is multiplied by a weighting factor ω_t^p, which is smaller than 1. Equation (18) corresponds to the profit of the future 4–8 h (*near future*). It consists of three parts: 1) income from the net output to the grid, 2) start-up and shutdown cost of pumping turbines in PSP, and 3) the penalty for the deviation between day-ahead and intraday bidding [as defined in (22)]. The latter two parts are subtracted from the profit. Equation (19) corresponds to the expected profit of the future 8–28 h (*farther future*). As wind power scenarios are used for the *farther future*, deviation in each scenario between output and intraday bidding is inevitable [as defined in (23)], which should be penalized [3]. Penalty factors of electricity price for positive/negative deviation between actual output and biddings, γ^+, γ^-, are set to the same value γ in this paper, which is the case in the German electricity market. The profit of *farther future* is the expectation of all scenarios, which are not the cases in (18). In the case of the *near future*, the intraday bidding is exactly the net output, as shown in (20).

Equation (21) is a chance constraint and it is equivalent to a deterministic constraint (37), as the probability density function of $\xi_t(v_t)$ is expressed by (38) [17]:

$$0 \le p_k^w \le p_k^{wf} + \xi_{v_k}^{-1}(\alpha) \tag{37}$$

$$f(x \mid \nu, \lambda, \mu) = \frac{\nu \lambda e^{-\nu(x-\mu)}}{\left(1 + e^{-\nu(x-\mu)}\right)^{\lambda+1}}. \tag{38}$$

Equation (24) limits the wind power fluctuation within predefined boundaries. Constraints for on/off state of pumping and generating are given in (25) while the number of pumping turbines at each interval is constrained by (26) and (27). Even though the start-up and shutdown of pumping turbines are considered in the objective function with start-up and shutdown costs, Equation (28) limits the total on-off frequency per day. Equations (29)–(32) define the pumping and generating power range of PSP, while the residue energy of PSP is constrained by (33)–(36).

3) Real-Time Control and Settlement: The WF-PSP union has following control targets in real-time operation. First of all, as the joint power output schedule was optimized in the intraday market, the union should keep the deviation between output and intraday biddings as little as possible, in order to minimize the settlement penalty. Secondly, fluctuation of joint output should not violate the corresponding standard. Last but not least, the energy of PSP should be observed and controlled in case that it were out of rated operational range. WF-PSP union's participation in frequency regulation and other ancillary services is not considered in this paper. The control scheme is shown as Fig. 3. The blocks of *WF output correction* and *PSP output correction* represent deviations between received instruction and actual output of WF and PSP, which need dynamic compensation:

$$\text{Min } \left(\overline{P_m^{\text{union}}} - P_m^{\text{bid}}\right)^2 + \omega^E \left(E_m - E_m^{\text{ref}}\right)^2 \quad m \in K \tag{39}$$

$$\overline{P_m^{\text{union}}} = \left(\sum_{k=\Delta t_m m}^{t_n} P_{k,a}^{\text{union}} + \sum_{k=t_n+1}^{\Delta t_m (m+1)} P_{k,\text{ins}}^{\text{union}} \right) \Bigg/ \Delta t_m \quad m \in K \tag{40}$$

$$p_{k,a}^{\text{union}} = p_{k,a}^w + p_{k,a}^g - p_{k,a}^p \quad k \in M \tag{41}$$

$$p_{k,\text{ins}}^{\text{union}} = p_{k,\text{ins}}^w + p_{k,\text{ins}}^g - p_{k,\text{ins}}^p \quad k \in M \tag{42}$$

$$-B_f^1 \le p_k^{\text{union}} - p_{k-1}^{\text{union}} \le B_f^1 \quad k \in M \tag{43}$$

$$-B_f^{10} \le F\left(p_{\text{k}}^{\text{union}}\right) \le B_f^{10} \tag{44}$$

$$0 \le p_k^w \le p_k^{wf} \quad k \in M \tag{45}$$

$$p_{\min} n_k^p \le p_k^p \le p_{\max} n_k^p \quad k \in M \tag{46}$$

$$s_k^g g_{\min} \le p_k^g \le s_k^g g_{\max} N \quad k \in M \tag{47}$$

$$E_{k+1} = E_k + p_k^p \Delta t \eta_c - p_k^g \Delta t / \eta_d \quad k \in M \tag{48}$$

$$E_{\min} \le E_k \le E_{\max} \quad k \in M. \tag{49}$$

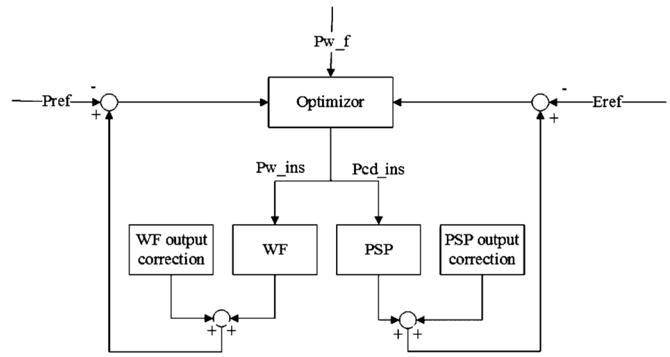

Fig. 3. Real-time operational block diagram.

Equation (39) defines the objective of real-time control, which is to bring near the intraday biddings and the average power in every 10 min, as well as make residue energy at the end of each interval as planned. Average power of each interval is calculated by (40). Equations (41) and (42) define the union instruction and output. Power change in 1 min and 10 min is restricted by (43) and (44) while (43) can be in the form of (2) or (3). Equation (45) restricts the wind power and the pumping and generating power range of PSP are determined by (46) and (47). Equation (48) and (49) have the residue energy of PSP in reasonable range.

Each of the above optimization problem is a mixed integer programming problem and can be solved by IBM ILOG Cplex® 12.5 within acceptable time length.

D. Handling Wind Power Forecast Error

1) Description of Wind Power Forecast Error: Wind power forecast errors are usually formulated as a Gaussian distribution. However, it is not always the case. Reference [18] studied the distribution of wind power forecast errors by simulation and maximal likelihood estimation, and found that the distribution varies with the forecast wind speeds. A versatile probability model of wind power forecast errors was put forward in [17], which can be easily applied in the chance constrained optimization. This paper describes the distribution of wind power forecast errors as a classified versatile probability function, which can reveal detailed information and transfer chance constraints to deterministic ones.

Wind power forecast errors obey different distributions at various forecast speeds [18]. When the forecast wind speed is much lower than the cut-in speed or higher than the rated speed, the forecast errors are very small. When the forecast speed is near the cut-in or rated speed, the distribution shows obvious skewness and can be described as an extreme distribution. When the forecast speed is in the middle of cut-in and rated speed, it is suitable to represent the errors as a Gaussian distribution. Probability density function of the versatile probability function proposed in [17] is (38). The cumulative density function and its inverse function is listed as follows:

$$F(x \mid \nu, \lambda, \mu) = \left(1 + e^{-\nu(x-\mu)}\right)^{-\lambda} \tag{50}$$

$$F^{-1}(c \mid \nu, \lambda, \mu) = \mu - \frac{1}{\nu} \ln(c^{-1/\lambda} - 1). \tag{51}$$

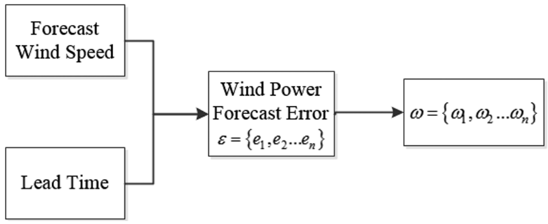

Fig. 4. Procedure for determining the weighting factor for *farther future* periods.

Equation (38) has two main advantages over common distributions such as Gaussian and Beta distribution. Firstly, it can represent different kinds of distribution with various parameters. Secondly, it has an explicit inverse function, which makes it easier to transfer the chance constraints to deterministic ones. In this paper, parameters of the function are fitted for every wind speed interval (1 m/s), in order to more precisely depict different wind power forecast errors at different speeds.

2) Determination of Weighting Factor: The forecast errors are affected not only by forecast wind speeds, but also by the time horizon (lead time). The influence of lead time on forecast error was studied in [10], which shows the forecast deviation increases linearly or weakly quadratically with lead time. In this paper, we assume this deviation increases linearly with lead time. So the forecast error related to wind speeds should be multiplied by the per-unit of forecast error variance proportional to the lead time, to determine the final forecast error, as shown in Fig. 4.

Weighting factors $\{\omega_t\}$ play an important role in intraday optimization. As mentioned above, ω_t reflects the influence of the forecast error, so it is a set of variables decided by the forecast errors [6], [19]. For a set of forecast errors $\varepsilon = \{e_1, e_2 \ldots e_n\}$, the corresponding weighting factor is defined as (52):

$$\omega_i = \exp\left\{-\frac{e_i - \min\{e_i\}}{\max\{e_i\} - \min\{e_i\}}\right\}. \tag{52}$$

IV. Case Studies

A. Basic Parameters

The proposed rolling optimization model is tested on a 495-MW WF group, which is in the northeast of China, and a 100-MW PSP. The PSP consists of five identical reversible pumping/generating turbines, whose basic parameters are given in Table II. Start-up and shutdown cost for each unit is set to 1000 RMB (RMB is the currency of China) per event [2]. Electricity prices are forecasted through historical data, and in this paper it is assumed that the forecast price is accurate. In some countries, the electricity price is determined by government and varies in different regions. It is presumed in the following tests that the price within the period of 9:00–23:00 is 0.8 RMB/kWh, and the price of the rest period is 0.4 RMB/kWh, which is based on the retail prices in some cities of China. As electricity prices are forecasted or given in advance, they are treated as constant in the optimization formulation.

The prices for a PSP to generate and consume energy are usually different if the PSP is not bidding in a power market. For example in China, there is no competing wholesale electricity market. Different PSPs may have different power generation and consumption prices to recovery their investment and operation costs. In the case of this paper, the optimal operation of PSP under deregulated power market environment is studied. The electricity generation and consumption wholesale prices are the same for the same place in a power market. The prices of generating and consuming energy for PSP are the same in some electricity markets such as the Spanish market [3]. The price variations will incentivize optimal operation of the PSP and other ESS to harvest more revenue through arbitrage.

The penalty factor γ for deviation between output and intraday bidding should be determined based on the balancing cost paid to other market participants, and is set equal to 0.44 [2]. The penalty to deviation between day-ahead and intraday biddings should represent the cost of rescheduling other generators. But as this penalty is not implemented in the actual power market, the factor β is set at a moderate 0.22 in the case studies, and results of sensitivity analysis will be given later.

TABLE II
Basic Parameters of PSP

$E_{\min}$ [MWh]	$E_{\max}$ [MWh]	$p_{\min}$ [MW]	$p_{\max}$ [MW]	$g_{\min}$ [MW]	$g_{\max}$ [MW]	η_c, η_d
50	500	18	22	10	25	0.9

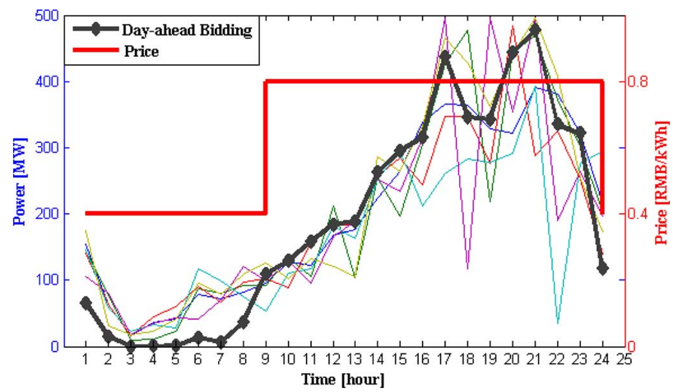

Fig. 5. Day-ahead optimal bidding of WF and PSP.

B. Time-Domain Demonstration

According to the proposed rolling optimization mechanism, the day-ahead bidding occurs at 12:00 of Day $(D-1)$, six intraday biddings occur every 4 h in Day D. The biddings, control strategies and settlements are all for Day D. Consequently, the test interval is one day.

Day-ahead bidding is illustrated in Fig. 5 as it is the premise of intraday bidding. The thin curves represent six distinct wind power scenarios that are simulated based on forecast results.

It can be seen from Fig. 5 that the PSP pumps water storing energy (the biddings are below the wind power forecasts) when electricity price is low, and generates when the price is high. Consequently in the valley period at 23:00–9:00, the bidding is less than the average forecast wind power and vice versa for peak periods.

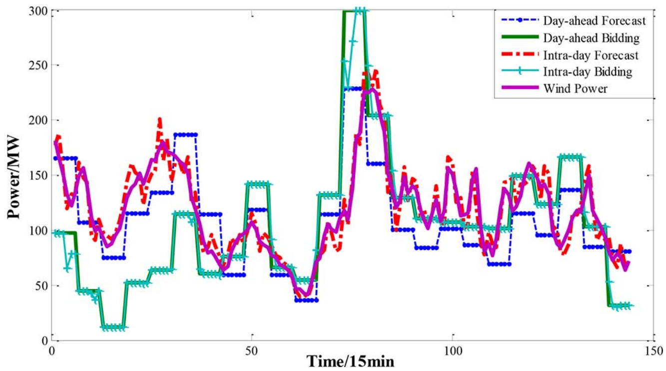

Fig. 6. Comparison of day-ahead and intraday biddings.

TABLE III
COMPARISON OF PROFIT WITH/WITHOUT INTRADAY MARKET (RMB)

Items	Sales Income	Startup/shut-down Cost	Deviation Penalty
Without intraday market	1 999 446	7 000	200 233
With intraday market	1 968 298	7 000	87 357
Items	**Rebidding Cost**	**Total Profit**	
Without intraday market	/	1 792 213	
With intraday market	9 982	1 863 959	

Fig. 6 compares the day-ahead and intraday biddings of a specific day. With more accurate wind power forecast, the WF-PSP union would revise its intraday bidding when the forecast difference exceeds some extent. With periodically updating the intraday bidding, the union can further reduce the deviation between the final bidding and its actual net output. By this means, the union can mitigate the penalty for output deviation and increase the aggregate profit.

C. Comparison of Profit

On one hand, with the help of intraday markets, the union can revise its biddings at a relatively low cost, which saves part of more expensive penalty for output deviation. On the other hand, PSP adjusts its output schedule of WF and PSP according to updated wind power forecast.

Take a specific day for example, Table III compares all the items that influence the total profit of the union. When there are intraday markets, deviation penalty decreases dramatically by over 50%, which majors the total profit improvement. The reduction of penalty comes at the cost of intraday rebidding cost, which is relatively little because of the lower penalty factor β. Comparing to the case without intraday markets, sales income drops by 1.5% with startup/shutdown cost unchanged. The total profit of WF-PSP union increases by 4.0 % with rolling optimization.

If running separately, the WF participates in the energy market alone and makes a profit through rolling optimization. PSP can make profit through arbitrage. The sum of the two parts is RMB 1 794 993 and lower than the profit of a joint operation by 3.70%, which provides the effectiveness of coordinated operation. Details of the profit comparison are listed in Table IV.

TABLE IV
PROFIT COMPARISONS WITH/WITHOUT COORDINATION (RMB)

Coordination	WF	PSP	Sum	Increase Rate
W/O	1 668 593	126 400	1 794 993	/
W	1 771 894	92 065	1 863 959	3.84%

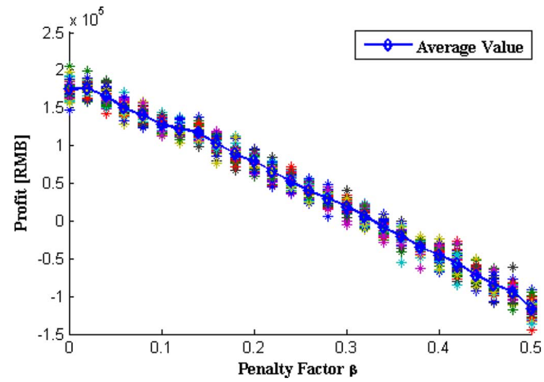

Fig. 7. Effects of bidding deviation penalty factor β has on the improved profit by intraday market.

It can be calculated from Table IV that the WF increases profit by 103 301 RMB through coordination while PSP's profit decreases by 34 335 RMB. In order to ensure that both participants can benefit from the coordination, WF should share partial increased profit with PSP. The transferred profit can be in the range from 34 335 to 103 301 RMB theoretically, but the actual subsidy will depend on the contract between WF and PSP.

D. Sensitivity Analysis

In order to study the influence that some parameters, such as reservoir volume, installed capacity and penalty factors, have on net profit, sensitivity analyses are carried out based on historical data. For simplicity of following discussion, we define *Scenario 1* as the case with day-ahead market only and *Scenario 2* as the case with rolling optimization of a complete set of day-ahead/intraday biddings and real-time operation. In the sensitivity analysis, profit of *Scenario 1* and *Scenarios 2* is compared at the same time.

1) Rebidding Penalty Factors: Penalty factor β for deviation between intraday and day-ahead biddings is essential to the intraday rebidding section. Fig. 7 demonstrates its influence on the profit improvement by intraday rebidding. For each value of β, 50 scenarios of wind power are simulated and the mean value is represented by the blue dots. When the factor is 0, the profit improvement is the value of updated wind power forecasts. When the penalty factor β is over 0.34, the profit of intraday bidding is even less than that of day-ahead market. It means that if only $\beta < 0.34$, WFs would get more profit through the intraday market. The turning point, $\beta = 0.34$ means that 34% of wind power deviation would be penalized for rescheduling other generators. In fact, adjusting cost for system operator is generally lower than 34% of the clearing price, which confirms the rationality and effectiveness of organizing an intraday market.

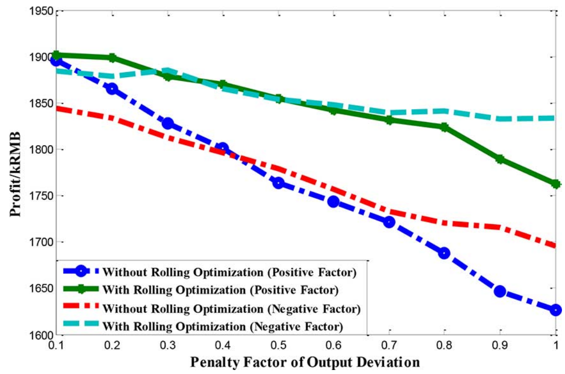

Fig. 8. Effects of output deviation penalty factor γ^+, γ^- on profit.

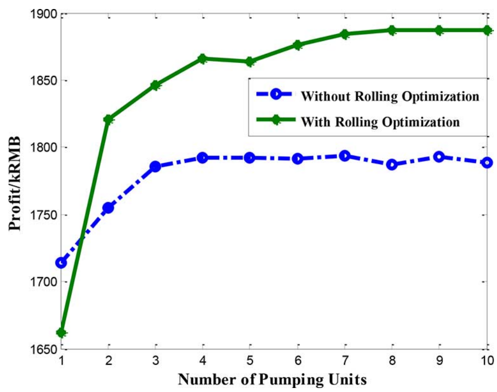

Fig. 9. Effects of PSP capacity on profit.

2) Penalty Factors of Output Deviation: It is clear from Fig. 8 that with the increase of positive/negative penalty factor, the profit of both *Scenario 1* and *2* drops gradually. *Scenario 2* is always occupying an advantage over *Scenario 1*, which demonstrates the meaning of rolling optimization in promoting profit of WF-PSP union. Besides, the influence of the positive factor on the total profit is more prominent than the negative factor. The phenomenon can be explained as follows: When the negative factor increases, the output deviation penalty increases but it also incents union to generate more, which partially compensates the penalty. However, the growth of positive penalty factor on one hand raises the deviation penalty, and on the other hand incents the union to reduce their output, which worsens the overall profit. Consequently, profit of WF-PSP union is more sensitive to the positive penalty factor than the negative one.

3) Installed Capacity of PSP: Fig. 9 shows that among all the parameters, overall installed capacity of PSP, namely the number of installed pumping/generating turbines, is the least flexible. Profit of *Scenario 2* will keep steady if there are over six turbines, because there is already enough regulating ability and other factors such as wind power forecast accuracy constrain the further improvement of profit. The phenomenon is more obvious for *Scenario 1* as the inflection point is three. The comparison also proves that the rolling optimization can better utilize the potential value of ESS.

4) Reservoir Volume of PSP: When the power capacity of PSP is fixed, the duration of pumping/generating at rated power is equivalent to the reservoir volume of PSP. Fig. 10 indicates that with the expansion of the reservoir, profit of *Scenario 1*

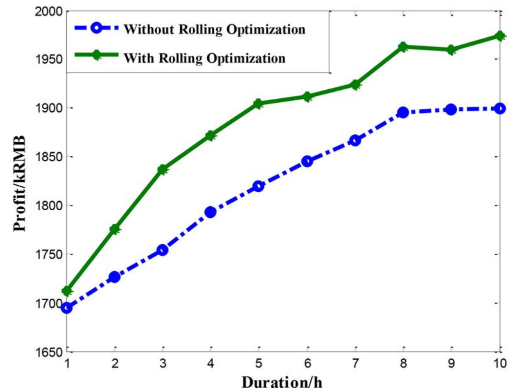

Fig. 10. Effects of reservoir volume of PSP on profit.

and *2* increases monotonously. When the duration reaches 8 h, profit will rise slowly, because the bottleneck comprises of other factors, such as the overall capacity and wind power forecast accuracy.

V. Conclusion

This paper puts forward a modified market design that allows for day-ahead bidding and intraday rebidding, which can better utilize updated wind power forecast information. The penalty for deviation between day-ahead and intraday bidding is set, which on one hand can encourage WFs to improve their forecast accuracy, and on the other hand can motivate the participants to revise their biddings in the intraday market with relatively low deviation penalty. This set of intraday market not only improves the profit of electricity market participants, but also helps reduce the dispatch pressure of system operator. The principle contributions of this paper are summarized as follows.

1) According to the proposed market mechanism, stochastic optimization models are formulated and solved to maximize the joint profit of WF-PSP union. In the intraday market optimization, the chance-constrained formulation is transferred to a deterministic one with the help of versatile probability function, which is used to express the wind power forecast error and has explicit inverse form.
2) As the forecast error increases notably with time horizon, this paper deals with the time periods of *near future* (4–8 h) and *farther future* (8–28 h) separately. It considers the coupling effect of *farther future* and also mitigate the impact of larger forecast error to the total profit.
3) Distributions of wind power forecast errors are formulated in detail. Without simply using Gaussian distribution, this paper classifies the wind power forecast errors according to forecast wind speeds. A versatile probability function which can imitate commonly used distributions is applied to depict the classified wind power forecast errors.

Case studies show that with the help of rolling optimization, the WF-PSP union can fully utilize the regulation capability of the PSP to increase the revenue. Compared to the case of running separately, the profit of coordinated operation has risen by 3.84%. Being allowed to revise biddings in the intraday market, the WF-PSP union can take advantage of updated wind power forecast information and further enhance the overall profit. The results are useful for the market designers and investors of WF and PSP.

In the end, sensitivity analyses are conducted to illustrate the influence that parameters such as PSP capacity and penalty factors have on the profit. The results show that in all tests, the union gains less profit in the case with day-ahead market only than in the case where there are day-ahead, intraday bidding sections and real-time operation. Furthermore, in both cases, profit grows with the increase of installed capacity and reservoir volume of PSP, and drops with the increase of penalty factor of bidding deviation and output deviation.

This work is meaningful to the design of the electricity market and the participants in deregulated markets, especially the renewable energy generators. Although the case studies are based on PSP, the application of proposed models can be extended to other kinds of ESS. In future, the constraints of the network will be considered as renewable resources and ESS may be distributed at different nodes of the power system.

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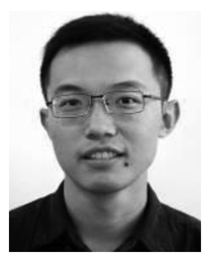

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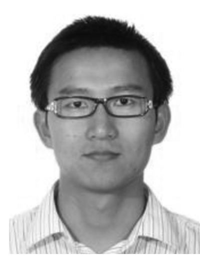

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