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Optimal Offering and Operating Strategies for Wind-Storage Systems With Linear Decision Rules

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Abstract—The participation of wind farm-energy storage systems (WF-ESS) in electricity markets calls for an integrated view of day-ahead offering strategies and real-time operation policies. Such an integrated strategy is proposed here by co-optimizing offering at the day-ahead stage and operation policy to be used at the balancing stage. Linear decision rules are seen as a natural approach to model and optimize the real-time operation policy. These allow enhancing profits from balancing markets based on updated information on prices and wind power generation. Our integrated strategies for WF-ESS in electricity markets are optimized under uncertainty in both wind power and price predictions. The resulting stochastic optimization problem readily yields optimal offers and linear decision rules. By adding a risk-aversion term in form of conditional value at risk into the objective function, the optimization model additionally provides flexibility in finding a trade-off between profit maximization and risk management. Uncertainty in wind power generation, as well as day-ahead and balancing prices, takes the form of scenario sets, permitting to reformulate the optimization problem as a linear program. Case studies validate the effectiveness of the strategy proposed by highlighting and quantifying benefits w.r.t. other existing strategies.

Index Terms—Bidding strategy, electricity markets, energy storage system, linear decision rules, real-time operation, wind farm.

I. INTRODUCTION

ALTHOUGH experiencing dramatic increase of installed capacity, wind power meets bottlenecks with integration into power systems. While it is increasingly accepted that wind power should directly participate in electricity markets, it faces substantial financial risks owing to its lack of controllability and predictability [1], which will result in variable and potentially large balancing costs. The optimal bidding for a wind farm (WF) participating in the electricity market as a price taker [2]

or a price maker [3] has been studied for many years. Generally in those works, the *Expected Utility Maximization* (EUM) strategy is fundamental in its simplest or extended forms [2], [4]. This strategy has the advantage of transparency and of low computational-costs since having a closed-form solution. In parallel, energy storage systems (ESS) are deemed promising for the support they could provide to WFs thanks to their flexible charging and discharging capability. The theme of coordinating wind farms and energy storage systems (abbreviated WF-ESS) has been the focus of many proposals over recent years. The main functions of ESS in these studies are to perform arbitrage in day-ahead markets, as well as to compensate for wind power deviations from schedule in real-time operation. For instance, a two-stage stochastic optimization model is described in [5] to maximize the profit of an WF-ESS in the Spanish electricity market, also giving general insight on mutual benefits from such coordination. Optimal offering in both day-ahead and intraday markets is studied in [6], where the real-time control strategy is to balance the wind power deviations as well as track the target residual energy of the ESS. ESS can also help flatten the variations of WF, as stated in [7]–[9].

Most papers assume that the role of ESS is to compensate for deviations from a pre-defined operation schedule and to smooth power output in real-time operation [10], [11]. These overlook the opportunity of optimizing market participation by optimally foreseeing how ESS could permit to jointly accommodate deviations from schedule and perform arbitrage. To prevent ESS from charging at high-price periods and discharging at low-price periods when balancing deviations, [12] proposes a reserve-based operation strategy for ESS, which allows ESS to balance the deviations of the WF within day-ahead contracted capacities. However, the day-ahead bidding of WF is optimized without considering the influence of ESS. Reference [13] extends this reserve-based strategy and embeds the balancing strategy into day-ahead optimization, which can prominently increase the profit of WF-ESS. These methods focus more on wind power deviations, while they are not very sensitive to balancing prices. In contrast, if aiming to integrate complicated real-time control strategies into day-ahead bidding optimization, traditional methods such as stochastic dynamic programming suffer from the exponential growth of computing efforts. Fortunately, linear decision rules permit to define decisions through affine transformation of realizations of uncertain parameters [14]–[16], hence keeping computational costs low. In this paper, we propose linear decision rules as real-time

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control strategies, where past, current and updated forecast information can be fully utilized and linearly combined to obtain optimal operation policies. This information includes deviations in day-ahead and balancing prices, as well as wind power generation, from their originally predicted values. Adopting linear decision rules as the real-time operation strategy permits to guarantee tractability while accommodating the dynamic nature of the operational problem [17].

Our main contribution consists of describing and evaluating an integrated strategy for day-ahead offering while accounting for the optimal operation of ESS at the balancing stage, where the real-time operation policy for the storage is modelled with linear decision rules. Optimal decision rules and day-ahead offers can be then obtained jointly. Our proposal is translated into a stochastic optimization problem where a trade-off is made between the expected profit maximization and the risk-aversion. Subsequently, discretization and linearization methods are employed to eventually obtain the solution of such stochastic optimization problems. Like most other works on this topic, our model neglects degradation costs of ESS,¹ while being developed under the assumption of being a price-taker in some European electricity markets, e.g., the Scandinavian Nord Pool. Another contribution relates to the quantification of the value of the residual energy of ESS. Furthermore, a sensitivity analysis is carried out to analyze the influence of price uncertainty and temporal correlation of wind power generation on profits. The Pareto efficient frontier is obtained to illustrate the trade-off between expected profit and risk.

The paper is organized as follows. Section II briefly introduces the basic rules of electricity markets, as well as our real-time operation strategy modelled through linear decision rules. The optimal offering and real-time operation policy is formulated as an integrated stochastic optimization problem in Section III. The objective function and constraints are further reformulated into linear ones to obtain optimal solutions. In Section IV, an illustrative case of two time intervals is firstly employed to illustrate the usage of linear decision rules. A comparison of the proposed strategy with other popular strategies is performed. Subsequently, we analyze how price uncertainty and wind power correlation affect market revenues, while the parameters such as constraint bandwidths and weighting factors are studied through a sensitivity analysis. Finally, conclusions and perspectives for future work are gathered in Section V.

II. LINEAR DECISION RULES FOR STORAGE-BASED IMBALANCE MANAGEMENT

A. Imbalance Management in Electricity Markets

Generally deregulated electricity markets consist of day-ahead and balancing market stages. For some power systems with a large proportion of renewable energies such as solar and wind power, adjustment or intraday markets may be of particular interest to correct for foreseen imbalances before the balancing stage [6]. As the trading amount of intraday markets is relatively small, it is not considered in this paper. Related work can be found in [18], [19].

¹The degradation cost could be readily complemented in the objective function as a linear term.

Day-ahead markets allow participants to bid for their generation schedule for the whole time horizons of the following day. These are cleared 10 to 12 hours prior to the first time interval for energy delivery of the following day. Such mechanism inevitably results in deviations between scheduled and actual generation, which is particularly severe for stochastic renewable energy generators [20]. If a deviation from schedule occurs, the generator should buy or sell up/down regulation services in the balancing market [13]. In this paper we do not consider the possibility for WF-ESS to additionally participate in ancillary service markets. For some electricity markets like the Dutch APX, balancing prices for up and down regulation services are the same and determined according to the overall system imbalance. In other power markets like Nord Pool and the Iberian one, up and down regulations are settled at different prices depending on whether their individual imbalance actually helps the system or not. More detailed descriptions and discussions on balancing markets can be found in [20]. In this paper, the models are built and illustrated based on one-price settlement in the balancing market. We will describe how these may be readily extended to the case of two-price settlement.

B. Linear Decision Rules for Real-Time Operation Policies

The whole time horizon (one day for example) can be discretized into T time intervals, usually with 1 hour for each interval and corresponding to the market time units. The state vector $\mathbf{x} = [x_1 \dots x_T]^\top \in \mathbb{R}^T$ stands for the residual energy of ESS at the end of each time interval. The state variables are temporally coupled as

$$x_t = x_{t-1} + \mathbf{B}\mathbf{u}_t, \quad t = 1, 2, \dots, T \quad (1)$$

where $\mathbf{B} = [0, \eta_c, -1/\eta_d]$ and x_0 is the initial residual energy. $\mathbf{u}_t = [p_t^w, p_t^c, p_t^d]^\top$ consists of the t th elements of wind power vector \mathbf{p}^w , charging power vector \mathbf{p}^c and discharging power vector \mathbf{p}^d , where $\mathbf{p}^w = [p_1^w \dots p_T^w]^\top \in \mathbb{R}^T$, $\mathbf{p}^c = [p_1^c \dots p_T^c]^\top \in \mathbb{R}^T$, $\mathbf{p}^d = [p_1^d \dots p_T^d]^\top \in \mathbb{R}^T$. η_c and η_d are charging and discharging efficiencies of the ESS.

According to linear decision rules, the power vectors of WF-ESS are determined by the affine function of day-ahead and balancing price forecast error, as well as wind power forecast error, i.e.,

$$\begin{bmatrix} \mathbf{p}^w \\ \mathbf{p}^c \\ \mathbf{p}^d \end{bmatrix} = \begin{bmatrix} \hat{\mathbf{p}}^w \\ \hat{\mathbf{p}}^c \\ \hat{\mathbf{p}}^d \end{bmatrix} + \begin{bmatrix} \mathbf{D}_{da}^w & \mathbf{D}_{rt}^w & \mathbf{D}_{wf}^w \\ \mathbf{D}_{da}^c & \mathbf{D}_{rt}^c & \mathbf{D}_{wf}^c \\ \mathbf{D}_{da}^d & \mathbf{D}_{rt}^d & \mathbf{D}_{wf}^d \end{bmatrix} \begin{bmatrix} \Delta\boldsymbol{\pi}^{da} \\ \Delta\boldsymbol{\pi}^{rt} \\ \Delta\boldsymbol{\pi}^w \end{bmatrix} \quad (2)$$

and can be denoted as $\mathbf{p} = \hat{\mathbf{p}} + \mathbf{D}\boldsymbol{\delta}$. $\hat{\mathbf{p}}$ is the nominal power vector and $\boldsymbol{\delta}$ is the vector consisting of forecast error for day-ahead prices $\Delta\boldsymbol{\pi}^{da}$, balancing prices $\Delta\boldsymbol{\pi}^{rt}$, and wind power generation $\Delta\boldsymbol{\pi}^w$. The affine matrix \mathbf{D} consists of 9 sub-matrices, which link power adjustments with forecast error of wind power and prices. Take \mathbf{D}_{rt}^w for example, it represents the influence of balancing price forecast error on wind power adjustment. We also denote $\mathbf{D}^w = [\mathbf{D}_{da}^w, \mathbf{D}_{rt}^w, \mathbf{D}_{wf}^w]$, $\mathbf{D}^c = [\mathbf{D}_{da}^c, \mathbf{D}_{rt}^c, \mathbf{D}_{wf}^c]$ and $\mathbf{D}^d = [\mathbf{D}_{da}^d, \mathbf{D}_{rt}^d, \mathbf{D}_{wf}^d]$, which are sub-matrices making up the matrix \mathbf{D} for later use. In the day-ahead optimization, as the forecast of wind power and prices are formulated by scenarios, the forecast error in (2) is the difference between the value of each scenario and their mean value.

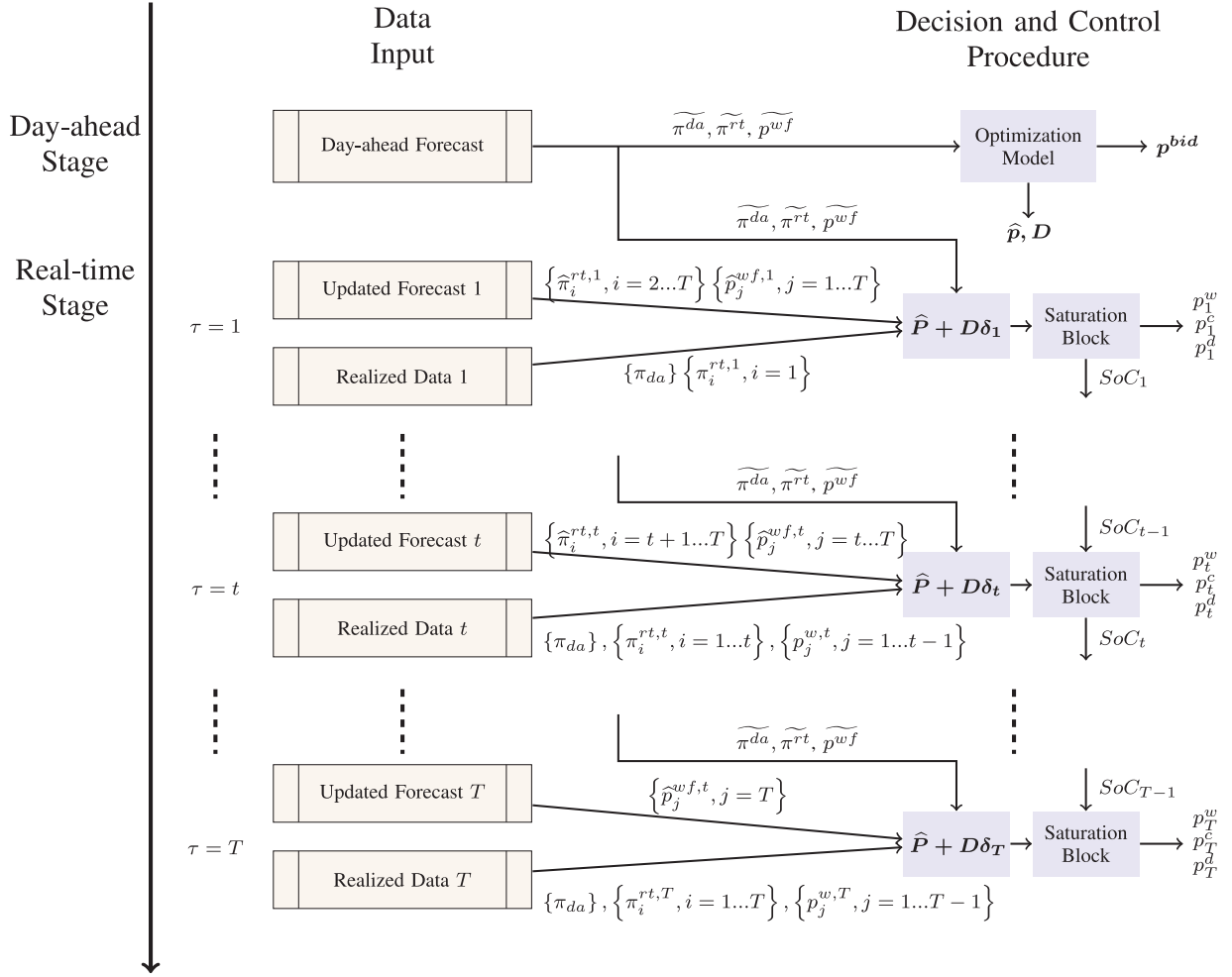


Fig. 1. Decision procedure and control of WF-ESS based on linear decision rules.

As shown in Fig. 1, linear decision rules are adopted for both day-ahead optimization and real-time operation. Denoted by $\tilde{\pi}^{da}$, $\tilde{\pi}^{rt}$ and \tilde{p}^{wf} , the forecast vectors of day-ahead prices, balancing prices and wind power are made 12–36 hours before the dispatch. These data are fed to the optimization model to obtain the optimal offering, p^{bid} , as well as the parameters of the linear decision rules, \hat{p} , D . Then \hat{p} and D are applied to the real-time operation. At time interval t , realizations of day-ahead prices, π^{da} , some balancing prices and wind power of the operating day, π^{rt} , p^w , are known, while the intraday forecasts of balancing prices and wind power $\hat{\pi}^{rt}$, \hat{p}^{wf} are updated. These data together with the day-ahead forecasts are used to determine the power output of WFs and ESS during real-time operation. Take the wind power in hour t for example, its decision is obtained as follows:

$$\begin{aligned}
 p_t^w &= \hat{p}_t^w + \sum_{i=1}^T D_{da,t,i}^w (\pi_i^{da} - \mathbb{E}(\tilde{\pi}_i^{da})) \\
 &+ \sum_{i=1}^t D_{rt,t,i}^w (\pi_i^{rt} - \mathbb{E}(\tilde{\pi}_i^{rt})) + \sum_{j=t+1}^T D_{rt,t,j}^w \Delta \mathbb{E}(\tilde{\pi}_j^{rt}) \\
 &+ \sum_{i=1}^{t-1} D_{wf,t,i}^w (p_i^w - \mathbb{E}(\tilde{p}_i^{wf})) + \sum_{j=t}^T D_{wf,t,j}^w \Delta \mathbb{E}(\tilde{p}_j^{wf})
 \end{aligned} \quad (3)$$

where $D_{da,t,i}^w$ is the element at row t , column i in matrix D_{da}^w . In addition, $\Delta \mathbb{E}(\tilde{\pi}_j^{rt}) = \mathbb{E}(\hat{\pi}_j^{rt}) - \mathbb{E}(\tilde{\pi}_j^{rt})$ and $\Delta \mathbb{E}(\tilde{p}_j^{wf}) = \mathbb{E}(\hat{p}_j^{wf}) - \mathbb{E}(\tilde{p}_j^{wf})$. Unlike the notation in Fig. 1, the superscripts indicating occurrence of update for $\{\hat{p}_j^{wf}\}$ and $\{\hat{\pi}_j^{rt}\}$ are omitted in (3) for the sake of succinctness. The charging or discharging decisions for ESS are made in a similar manner, simply replacing the up-script ‘ w ’ of p and D in the above with ‘ c ’ or ‘ d ’.

The decision about power output at any time interval consists of four parts, as in (3). The first part is the nominal power \hat{p}_t^w , determined from the day-ahead offering stage. The second part corresponds to the influence of the day-ahead price forecast error, while the last two parts (corresponding to the last two lines) are for the influence of the forecast error in the balancing prices and real-time available wind power generation. When it comes to real-time, the day-ahead prices $\{\pi_i^{da}\}$ for the whole time horizon are known. However, the balancing prices $\{\pi_i^{rt}\}$ and the available wind power $\{p_i^w\}$ are only accessible for the past hours, $\{i = 1 \dots t\}$. Consequently, those for the following intervals, $\{i = t + 1, \dots, T\}$, should be substituted with the expectation of updated forecast $\{\mathbb{E}(\hat{\pi}_i^{rt})\}$ and $\{\mathbb{E}(\hat{p}_i^{wf})\}$ to obtain the deviations. It should be noted that for each time interval, the latest updated $\hat{\pi}^{rt}$, \hat{p}^{wf} are used.

Stochastic parameters are commonly dealt with by constraining their potential realizations within specific uncertainty sets, around their expectation [14]. Although the polyhedron is a good choice to describe uncertainty sets, if the given prices and wind power forecasting error were too large, the only feasible matrix \mathbf{D} would be an all-zero matrix. Then the strategy could not react to the real time information, and the strategy on linear decision rules would lose its value. In order to prevent this from happening, the formulation of uncertainty sets is tightened here, which will result in the decision vector \mathbf{u} violating the operation constraints of WF-ESS systems during operation. The violation comes from the fact that \mathbf{D} and $\hat{\mathbf{p}}$ are pre-determined, while $\boldsymbol{\delta}$ is a random vector, which cannot be completely simulated by scenarios, or perfectly formulated by polyhedral constraints due to above-mentioned reasons. Consequently, a checking through a saturation block is necessary to constrain the charging and discharging power of ESS. As illustrated in Fig. 1, the charging and discharging power of ESS obtained through linear decision rules, as well as state of charge (SoC) is fed to the saturation block, to prevent the ESS from over-charging or over-discharging. At any time, the charging and discharging power should be limited so as not to drive the residual energy out of the allowable ranges at the next time interval. Consequently, the charging threshold is $\min\left\{\bar{p}_c, \frac{E_{\max} - E_t}{\eta_c \Delta t}\right\}$, and the discharging threshold is $\min\left\{\bar{p}_d, \frac{E_t - E_{\min}}{\Delta t} \eta_d\right\}$. As the saturation block changes the power output only in extreme situations, which occurs rarely, it does not have much influence on the overall profit. Consequently, the saturation block is not included in the optimization model.

III. FORMULATION OF THE OPTIMAL OFFERING STRATEGY

When determining the optimal day-ahead offering, the WF-ESS should not only pursue the higher expected profit but also reduce the potential risk. In our strategy, the risk is formulated by conditional value at risk (CVaR), and is co-optimized with the expected profit through linear combination. The optimization problem can be formulated as,

$$\max_{\boldsymbol{\theta}} \quad \gamma \mathbb{E} \left(\tilde{S}(\boldsymbol{\theta}, \boldsymbol{\delta}) \right) + (1 - \gamma) \text{CVaR}_{\alpha} \left(\tilde{S}(\boldsymbol{\theta}, \boldsymbol{\delta}) \right) \quad (4a)$$

$$\text{s.t.} \quad g(\boldsymbol{\theta}, \boldsymbol{\delta}) \leq 0 \quad (4b)$$

where $\boldsymbol{\theta} = \{\mathbf{p}^{bid}, \mathbf{D}, \hat{\mathbf{p}}\}$ are decision variables. \mathbf{p}^{bid} is the vector of day-ahead offers p_t^{bid} . It should be noted here that as the wind-storage system adopts the price-taker strategy, it will bid at zero or slightly negative prices to guarantee itself to be cleared out and to get paid at the cleared prices. Consequently it only needs to determine the optimal quantity to offer. The objective function considers the expectation and risk of the WF-ESS profit, while (4b) constrains power of WF and ESS, residual energy of ESS, and offering quantities.

The constraint set $g(\boldsymbol{\theta}, \boldsymbol{\delta}) \leq 0$ is built to guarantee the feasibility of solutions for any realization of $\boldsymbol{\delta}$ within a certain neighborhood of the forecast value \mathbf{d}_0 . The uncertainty set is defined as $\mathbf{H}\boldsymbol{\delta} \leq \mathbf{h}$, where $\mathbf{H} = [I_{3T}, -I_{3T}]^{\top}$, $\mathbf{h} = [\delta^+ \mathbf{1}_{3T}, -\delta^- \mathbf{1}_{3T}]^{\top} \mathbf{d}_0$. δ^+ and δ^- are up/down deviation factor to the forecast value. I_{3T} , $\mathbf{1}_{3T}$ are a 3T-dimensional unit

matrix and a $3T \times 1$ column vector with all elements set to 1, respectively. Constraints in (4b) include

$$E_{\min} \leq \mathbf{x}(\boldsymbol{\theta}, \boldsymbol{\delta}) \leq E_{\max} \quad (5)$$

$$\underline{p}^c \leq \mathbf{D}^c \boldsymbol{\delta} + \hat{\mathbf{p}}^c \leq \bar{p}^c \quad (6)$$

$$\underline{p}^d \leq \mathbf{D}^d \boldsymbol{\delta} + \hat{\mathbf{p}}^d \leq \bar{p}^d \quad (7)$$

$$0 \leq \mathbf{D}^w \boldsymbol{\delta} + \hat{\mathbf{p}}^w \leq \mathbf{p}^{wf} \quad (8)$$

$$0 \leq \mathbf{p}^{bid} \leq C^w \quad (9)$$

Equation (5) limits the residual energy of ESS at each interval within allowable ranges $[E_{\min}, E_{\max}]$. The same goes for the charging and discharging power of ESS, as in (6) and (7), with lower and upper levels of charging and discharging power, $[\underline{p}^c, \bar{p}^c]$ and $[\underline{p}^d, \bar{p}^d]$, respectively. Moreover, considering the possibility of curtailing wind power generation, (8) indicates that the actual wind power output will not exceed the real-time forecast value, \mathbf{p}^{wf} . The offered amount should be nonnegative as the role of WF-ESS is a generator in the market, and the amount should be below the allowable integration capacity of WF-ESS, C^w , given by (9). In references such as [16], components of the decision matrix \mathbf{D} , such as \mathbf{D}_{rt}^c , are set as lower triangular matrices as future information is not available at any given time. However here, future information is substituted with updated forecast values for the balancing price and wind power related matrices. Hence corresponding matrices do not have to be lower-triangular. Moreover, the day-ahead price related matrices, such as \mathbf{D}_{da}^c , is not lower triangular as day-ahead prices have already been determined before operation.

A. Details of the Objective Function

The objective of WF-ESS is to maximize total profit from both day-ahead and balancing stages. Besides the expected profit, risk is another important issue to consider in the management of WF-ESS. $\mathbb{E} \left(\tilde{S}(\boldsymbol{\theta}, \boldsymbol{\delta}) \right)$ denotes the expected profit driven by the uncertainty of $\boldsymbol{\delta}$, while $\text{CVaR}_{\alpha} \left(\tilde{S}(\boldsymbol{\theta}, \boldsymbol{\delta}) \right)$ is CVaR at the confidence level of α .

The objective function controls the trade-off between the expectation and CVaR with a parameter $\gamma \in [0, 1]$. Setting $\gamma = 0$ yields the totally risk-averse case. Increasing the value of γ makes the strategy more risk-neutral, with eventually $\gamma = 1$ representing the completely risk-neutral case. More specifically, the profit $\tilde{S}(\boldsymbol{\theta}, \boldsymbol{\delta})$ can be expressed as

$$\tilde{S}(\boldsymbol{\theta}, \boldsymbol{\delta}) = \sum_{t=1}^T \left[\tilde{\pi}_t^{da} p_t^{bid} + \tilde{\pi}_t^{rt} (p_t^{out} - p_t^{bid}) \right] + \tilde{\pi}^E \Delta E \quad (10)$$

where p_t^{out} is the joint output of WF-ESS at time interval t , and $p_t^{out} = [1, -1, 1] \mathbf{u}_t$. The profit consists of three parts. The first part $\tilde{\pi}_t^{da} p_t^{bid}$ is the profit from day-ahead offering, while the second part $\tilde{\pi}_t^{rt} (p_t^{out} - p_t^{bid})$ is the profit or penalty from the balancing market.

The last term in (10) is the so-called *energy value*. Unlike most papers where residual energy of ESS at the end of the scheduling horizon is either overlooked or anchored within an acceptable deviation from initial level [13], we use the concept of *energy value* to reflect the value of the residual energy in ESS, since the residual energy has the potential to yield profits by generating (discharging) in following horizons. It is inspired by

an essential concept, *water value* in hydro-power management, which relates to the marginal cost of water in the reservoirs, and is equal to the replacement value of other general generators or average market prices in ideal cases. Energy value introduced here is to reflect the influence of residual energy on the daily profit. Consequently, for the sake of simplicity, the final residual energy deviation of ESS, $\Delta E = x_T - x_0$, is assigned a price, $\tilde{\pi}^E$, to reflect its value, and the resulting energy value is considered in the objective function of (10). Substituting (2) into (10), the stochastic profit function can be reformulated as

$$\begin{aligned} \tilde{S}(\theta, \delta) = & \tilde{\pi}^{rt} \left[\left(\mathbf{D}^w + \mathbf{D}^d - \mathbf{D}^c \right) \delta + \left(\hat{\mathbf{p}}^w + \hat{\mathbf{p}}^d - \hat{\mathbf{p}}^c \right) \right] \\ & + \left(\tilde{\pi}^{da} - \tilde{\pi}^{rt} \right) \mathbf{p}^{bid} + \tilde{\pi}^E \Delta E \end{aligned} \quad (11)$$

where $\tilde{\pi}^{da}$ and $\tilde{\pi}^{rt}$ are vectors of $\tilde{\pi}_t^{da}$ and $\tilde{\pi}_t^{rt}$.

B. Reformulation of the Objective Function

CVaR is defined as in [20],

$$\text{CVaR}_\alpha(s) = \mathbb{E} \{s | s \leq \text{VaR}_\alpha(s)\} = \frac{1}{\alpha} \int_0^{\text{VaR}_\alpha(s)} sp(s) ds \quad (12)$$

where $S(\theta, \delta)$ is denoted by s for convenience. $p(s)$ is the probability density function of the random variable s and VaR_α is defined as

$$\text{VaR}_\alpha(s) = \min \{V \in \mathbb{R} : P(s \leq V) \geq \alpha\} \quad (13)$$

where $P(s)$ is the cumulative distribution function of s .

Such definition of VaR can make it difficult to handle CVaR. Inspired by the work of [21], we define a simpler function

$$F(s, v, \alpha) = v + \frac{1}{\alpha} \int_{s < v} (s - v) p(s) ds \quad (14)$$

whose maximum with regard to (w.r.t) v can be used as CVaR. Here we provide a simple explanation. Detailed and strict proof can be found in [22], [23]. The derivative of (14) w.r.t v is

$$\frac{\partial F(s, v, \alpha)}{\partial v} = 1 - \frac{1}{\alpha} \int_{s < v} p(s) ds.$$

By equating it to 0, we can obtain that VaR maximizes $F(s, v, \alpha)$ w.r.t v (the second order derivative of F w.r.t v as $\frac{-1}{\alpha} p(v)$ is negative). Furthermore, the maximum of function $F(s, v, \alpha)$ w.r.t v is equal to CVaR.

In our optimization problem formulation, uncertain prices and wind power output in the objective function are represented by scenarios. Define Ω as the set of scenarios, ρ_ω as the probability for scenario ω , and $\sum_{\omega \in \Omega} \rho_\omega = 1$, then the expectation can be formulated as

$$\mathbb{E}(\tilde{S}(\theta, \delta)) = \sum_{\omega \in \Omega} \rho_\omega S_\omega \quad (15)$$

where

$$\begin{aligned} S_\omega = & \pi_\omega^{rt} \left[\left(\mathbf{D}^w + \mathbf{D}^d - \mathbf{D}^c \right) \delta_\omega + \left(\hat{\mathbf{p}}^w + \hat{\mathbf{p}}^d - \hat{\mathbf{p}}^c \right) \right] \\ & + \left(\pi_\omega^{da} - \pi_\omega^{rt} \right) \mathbf{p}^{bid} + \pi_\omega^E \Delta E_\omega. \end{aligned}$$

π_ω^{rt} is the realization of the real-time price under scenario ω , while the same goes for the variables such as δ_ω , π_ω^{da} , π_ω^E and ΔE_ω . Equation (14) can be discretized as:

$$\text{CVaR}_\alpha \left(\tilde{S}(\theta, \delta) \right) = v + \frac{1}{\alpha} \sum_{\omega \in \Omega} \rho_\omega [S_\omega - v]^- \quad (16)$$

where $[x]^- = \min\{x, 0\}$. By introducing the slack variables $\{z_\omega\}$, we can linearize (16) as

$$\begin{cases} \text{CVaR}_\alpha \left(\tilde{S}(\theta, \delta) \right) = v + \frac{1}{\alpha} \sum_{\omega \in \Omega} \rho_\omega z_\omega \\ z_\omega \leq S_\omega - v \\ z_\omega \leq 0. \end{cases} \quad (17)$$

Substituting (15) and (17) into (4a), the objective function can be reformulated linearly as

$$\max_{\theta} \quad \gamma \sum_{\omega \in \Omega} \rho_\omega S_\omega + (1 - \gamma) \left(v + \frac{1}{\alpha} \sum_{\omega \in \Omega} \rho_\omega z_\omega \right) \quad (18a)$$

$$\text{s.t.} \quad z_\omega \leq S_\omega - v, \quad z_\omega \leq 0 \quad (18b)$$

$$\begin{aligned} S_\omega = & \pi_\omega^{rt} \left[\left(\mathbf{D}^w + \mathbf{D}^d - \mathbf{D}^c \right) \delta_\omega + \left(\hat{\mathbf{p}}^w + \hat{\mathbf{p}}^d - \hat{\mathbf{p}}^c \right) \right] \\ & + \left(\pi_\omega^{da} - \pi_\omega^{rt} \right) \mathbf{p}^{bid} + \pi_\omega^E \Delta E_\omega, \quad \forall \omega \in \Omega. \end{aligned} \quad (18c)$$

C. Reformulation of Constraints

Constraint (5) can be reformulated as

$$\begin{bmatrix} I_T \\ -I_T \end{bmatrix} \begin{pmatrix} x_0 \mathbf{1}_T + I_{dr,T} \left(\eta_c \hat{\mathbf{p}}^c - \frac{1}{\eta_d} \hat{\mathbf{p}}^d \right) \\ + I_{dr,T} \left(\eta_c \mathbf{D}^c - \frac{1}{\eta_d} \mathbf{D}^d \right) \delta \end{pmatrix} \leq \begin{bmatrix} \mathbf{1}_T E_{\max} \\ -\mathbf{1}_T E_{\min} \end{bmatrix} \quad (19)$$

where $I_{dr,T}$ is a T-dimensional lower triangular matrix with all elements as 1. Similarly, constraint (6) to (8) can be reformulated as

$$\begin{bmatrix} I_T \\ -I_T \end{bmatrix} \hat{\mathbf{p}}^c + \begin{bmatrix} I_T \\ -I_T \end{bmatrix} \mathbf{D}^c \delta \leq \begin{bmatrix} \mathbf{1}_T \bar{p}^c \\ -\mathbf{1}_T \underline{p}^c \end{bmatrix} \quad (20)$$

$$\begin{bmatrix} I_T \\ -I_T \end{bmatrix} \hat{\mathbf{p}}^d + \begin{bmatrix} I_T \\ -I_T \end{bmatrix} \mathbf{D}^d \delta \leq \begin{bmatrix} \mathbf{1}_T \bar{p}^d \\ -\mathbf{1}_T \underline{p}^d \end{bmatrix} \quad (21)$$

$$\begin{bmatrix} I_T \\ -I_T \end{bmatrix} \hat{\mathbf{p}}^w + \begin{bmatrix} \mathbf{D}^w - [0, 0, I_T] \\ -\mathbf{D}^w \end{bmatrix} \delta \leq \begin{bmatrix} [0, 0, I_T] \mathbf{d}_0 \\ 0 \end{bmatrix} \quad (22)$$

Furthermore, constraints (19)–(22) can be reformulated in order to eliminate the random variable δ and to have finite cardinality through duality theory, as performed by [16]. More specifically, these constraints can be presented in an abstract way as $\mathbf{c}^\top \delta \leq q$ with any δ satisfying $\mathbf{H} \delta \leq \mathbf{h}$. This yields

$$\max_{\delta} \left\{ \mathbf{c}^\top \delta, \text{s.t. } \mathbf{H} \delta \leq \mathbf{h} : \boldsymbol{\mu} \right\} \leq q \quad (23)$$

where $\boldsymbol{\mu}$ is the dual variable associated with the constraints. According to duality theory, (23) is equivalent to

$$\begin{aligned} \exists \quad & \boldsymbol{\mu} \geq 0 \\ \text{s.t.} \quad & \boldsymbol{\mu}^\top \mathbf{h} \leq q \\ & \boldsymbol{\mu}^\top \mathbf{H} = \mathbf{c} \end{aligned} \quad (24)$$

D. Final Form and Possible Extensions

Finally, the whole problem is formulated in a linear way as,

$$\begin{aligned} \max \quad & (18a) \\ \text{s.t.} \quad & (18b), (18c) \\ & (19) - (22) \text{ in form of (24)}. \end{aligned}$$

It should be noted that the formulation above is based on the one-price balancing market, while this can be readily extended to the two-price case. This is done by replacing the profit $\tilde{S}(\theta, \delta)$ in (10) with the following one,

$$\begin{cases} \sum_{t=1}^T [\tilde{\pi}_t^{da} p_t^{bid} - \tilde{\pi}_t^{rt+} p_t^{up} + \tilde{\pi}_t^{rt-} p_t^{dw}] + \tilde{\pi}^E \Delta E \\ p_t^{dw} - p_t^{up} = p_t^{out} - p_t^{bid} \\ p_t^{dw}, p_t^{up} \geq 0 \end{cases} \quad (25)$$

where $\tilde{\pi}_t^{rt+}, \tilde{\pi}_t^{rt-}$ are up- and down-regulation prices and p_t^{dw}, p_t^{up} are positive and negative deviations between actual output and day-ahead offer. Either p_t^{dw} or p_t^{up} should be 0 due to the optimization requirement. This characteristic ensures that p_t^{dw} or p_t^{up} can precisely represent the down-regulation and up-regulation power capacity. Detailed proof can be found in [24], where a similar reformulation was proposed and employed. However, for the sake of simplicity and transparency, the solution approach presented above and the following case studies are both based on the one-price balancing market case.

IV. APPLICATION RESULTS

In this section, case design is firstly introduced in IV.A. Then two case studies are carried out. The first case with two time intervals is presented in IV.B, which aims for a more lucid demonstration of the proposed integrated strategy, especially the linear decision rules. Furthermore, the second case study with 24 time intervals compares profits brought by different strategies in IV.C, and sensitivity analyses of related parameters are performed in IV.D.

A. Case Design

Both case studies are based on realistic data from the Nord Pool market [25] and wind farms in Denmark [26], [27]. Per-unit data of wind power forecast scenarios are provided by [28] and translated into actual data by multiplying C_w . These 100 scenarios are applied to optimization, and also used to fit distributions of wind power at each time interval. Then quantities of wind power scenarios for evaluation of strategies and sensitivity analyses are generated based on these distributions, as performed in [13].

Day-ahead prices and up/down-regulation prices are from the DK-West area in the Nord Pool market during January 1st to 10th, 2014. Because the Nord Pool is of two-price balancing market, up/down-regulation prices are different and one or the other of them is equal to the day-ahead price at any specific time interval. So we take the different one as the balancing price in the one-price balancing market. Similarly, price scenarios are

TABLE I
PARAMETERS OF THE WF-ESS SYSTEM

η_c	η_d	E_{min} [MWh]	E_{max} [MWh]
0.95	0.95	10	50
E_0	\bar{p}^c [MW]	\bar{p}^d [MW]	C_w [MW]
30	10	10	100

necessary for both optimization and strategy evaluation, and they are generated as

$$\begin{aligned} \tilde{\pi}_t^{da} &= \bar{\pi}_t^{da} (1 + \sigma_{da} \tilde{\varepsilon}) \\ \tilde{\pi}_t^{rt} &= \bar{\pi}_t^{rt} (1 + \sigma_{rt} \tilde{\varepsilon}) \end{aligned} \quad (26)$$

where $\bar{\pi}_t^{da}, \bar{\pi}_t^{rt}$ are actual data of the day-ahead and balancing prices at time interval t . $\tilde{\varepsilon}$ is a random variable which obeys the standard normal distribution $\tilde{\varepsilon} \sim N(0, 1)$, and σ_{da} and σ_{rt} are the standard deviations for day-ahead and balancing prices. The *energy value* of an ESS is updated every day and set as the average spot price, as stated in most papers in the field of hydro-generator [29]. Parameters of ESS are listed in Table I. In following case studies, primary parameters are set as: $\gamma = 0.9, \Delta^+ = -\Delta^- = 0.1, \sigma_{da} = 0.2, \sigma_{rt} = 0.3$ and $\alpha = 0.05$.

B. An Illustrative Case

In this case, the first two intervals of wind power and price data generated in IV.A are applied. The optimal solution is $\hat{p}^w = [52.9, 59.3]^\top, \hat{p}^c = [5, 5]^\top, \hat{p}^d = [5, 5]^\top, D_c^{rt} = \begin{bmatrix} -2.17 & 0 \\ 0 & -2.34 \end{bmatrix}, D_d^{rt} = \begin{bmatrix} 0.15 & -2.17 \\ -2.17 & 0 \end{bmatrix}, D_w^{wf} = \begin{bmatrix} 1, & 0 \\ 0, & 1 \end{bmatrix}$, while $D_c^{da}, D_c^{wf}, D_d^{da}, D_d^{wf}, D_w^{da}, D_w^{rt}$ are all zeros. From the results we can see scheduled wind power is independent from prices, while charging and discharging power of ESS only depend on balancing prices.

Assume that wind power forecast error $\Delta p^w = [6, 7]$ MW, day-ahead price forecast error $\Delta \pi^{da} = [1, 2]$ EUR/MWh, while balancing price forecast error $\Delta \pi^{rt} = [-1, 1]$ EUR/MWh. According to (3), charging and discharging power of intervals can be expressed as

$$\begin{aligned} p_1^w &= 52.9 + 1 \times 6 = 58.9 \text{ MW} \\ p_2^w &= 59.3 + 1 \times 7 = 66.3 \text{ MW} \\ p_1^c &= 5 + (-2.17) \times (-1) = 7.17 \text{ MW} \\ p_2^c &= 5 + (-2.34) \times 1 = 2.66 \text{ MW} \\ p_1^d &= 5 + 0.15 \times (-1) + (-2.17) \times 1 = 2.68 \text{ MW} \\ p_2^d &= 5 + (-2.17) \times (-1) = 7.17 \text{ MW}. \end{aligned}$$

Since simultaneous charging and discharging is prohibited and $p_1^c > p_1^d$, the actual discharging power of the first interval $p_1^{d'}$ is 0, while the amended charging power is $p_1^{c'} = p_1^c - p_1^d = 4.49$ MW. Then in the second time interval, as $p_2^c < p_2^d$, the amended charging power $p_2^{c'} = 0$ and discharging power $p_2^{d'} = p_2^d - p_2^c = 4.51$ MW. The power decision procedure of WF and ESS can be extended to cases of more time intervals.

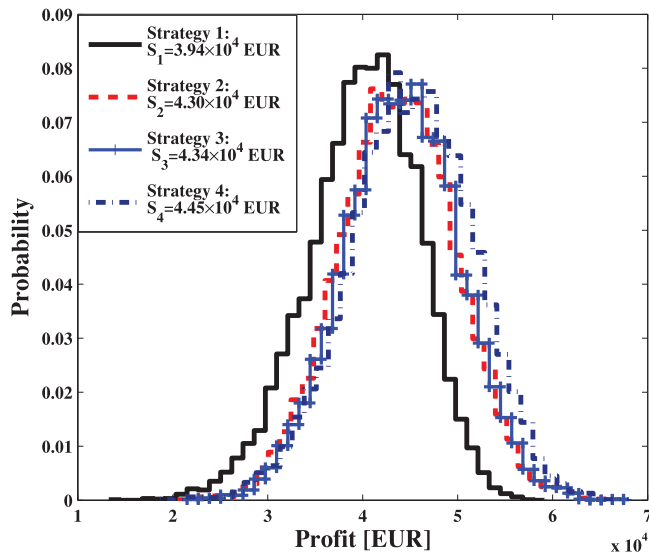


Fig. 2. The distributions of profit over scenarios for all strategies, based on 10000 scenarios.

C. Profit Comparison

The profit earned by the proposed strategy is compared with some other commonly adopted strategies. Strategy 1 is used as a benchmark, which bids the forecast value and generates without any curtailments for a wind farm operating alone. Strategy 2 is the *Expected Utility Maximization* (EUM) strategy, where the WF bids the optimal quantile of wind power forecast and generates without any curtailment [2]. In both strategies, the WF works alone without the ESS. Strategy 3 is the *Filter Control Strategy* (FCS) [11], where the ESS is utilized to compensate for the deviations between wind power output and day-ahead bidding to reduce the deviation penalty cost. Strategy 4 is the proposed linear-decision-rules one.

The comparisons are carried out using 10000 test scenarios in a Monte Carlo simulation framework. The distributions of profit over all the scenarios for the strategies are demonstrated in Fig. 2, while the mean values of profits obtained by strategies are also listed on the figure. Several conclusions can be reached from the comparison. Firstly, when the WF operates alone, the EUM strategy can help enhance the profit (compare Strategy 1 and Strategy 2). Secondly, the FCS does not have obvious advantages over the EUM strategy, which confirms the conclusion in paper [13] that only with proper control strategy can ESS bring satisfactory profit. Thirdly, the proposed control strategy has the best economic profit as the probability distribution shifts right obviously, which increases the profit of wind farm by over 11%.

D. Sensitivity Analysis

Parameters of the model will significantly influence the result of the formulations. Two key parameters, bandwidth of the uncertainty, $\Delta^+ - \Delta^-$, and the weighting factor γ are firstly studied in this section. The uncertainty bounds of prices and wind power are defined by the polyhedral formulation $\mathbf{H}\delta \leq \mathbf{h}$, where \mathbf{h} is equal to the product of \mathbf{d}_0 and the vector of positive

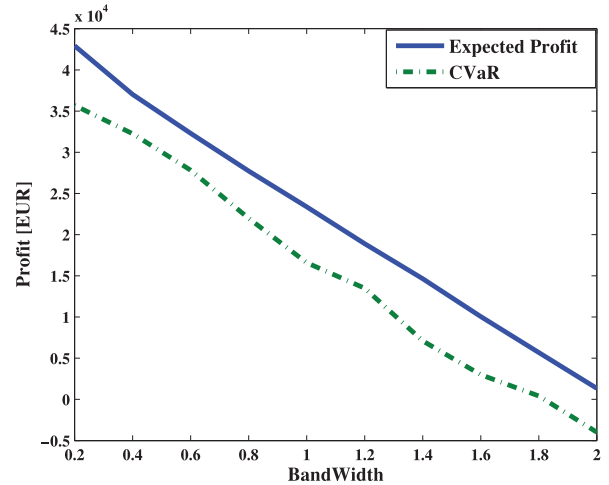


Fig. 3. Sensitivity analysis of bandwidth of robust optimization.

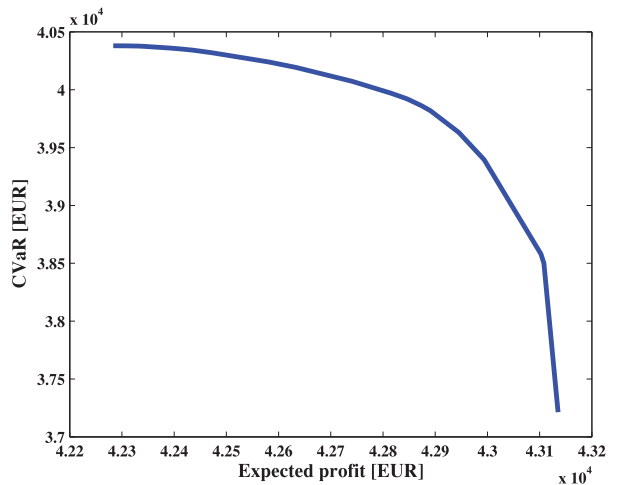


Fig. 4. The Pareto frontier of the profit (all the feasible region is under the blue curve).

and negative parameters Δ^+ and Δ^- . Consequently we define $\Delta^+ - \Delta^-$ as the uncertainty bandwidth and investigate its influence on final results. It can be seen from Fig. 3 that with the increase of uncertainty bandwidth, the expectation and CVaR of profit decreases monotonously. This is because that a larger uncertainty bandwidth requires the solution be feasible for more possible realizations of uncertain scenarios, which narrows feasible region of the optimization problem. Consequently it is natural that the optimality of the formulation decreases with the shrinking feasible region.

Another essential parameter of the formulation is the weighting factor γ , which makes the trade-off between the expected profit and risk. As explained in III.A, a larger γ implies a more risk-neutral strategy. Table II shows that an increasing weighting factor can better guarantee the expected profit but sacrifices the CVaR. The value selection of γ depends on the attitude of the WF-ESS to risk and each value of γ maps to one point of the Pareto efficient frontier in Fig. 4, which means there does not exist any solution which can make both expectation and CVaR better off at the same time.

TABLE II
SENSITIVITY ANALYSIS OF WEIGHTING FACTOR

γ	Expectation [kEUR]	CVaR [kEUR]
0	42.28	40.38
0.1	42.33	40.38
0.2	42.34	40.38
0.3	42.42	40.35
0.4	42.47	40.32
0.5	42.63	40.19
0.6	42.82	39.97
0.7	42.87	39.86
0.8	42.95	39.63
0.9	43.10	38.58
1.0	43.14	37.21

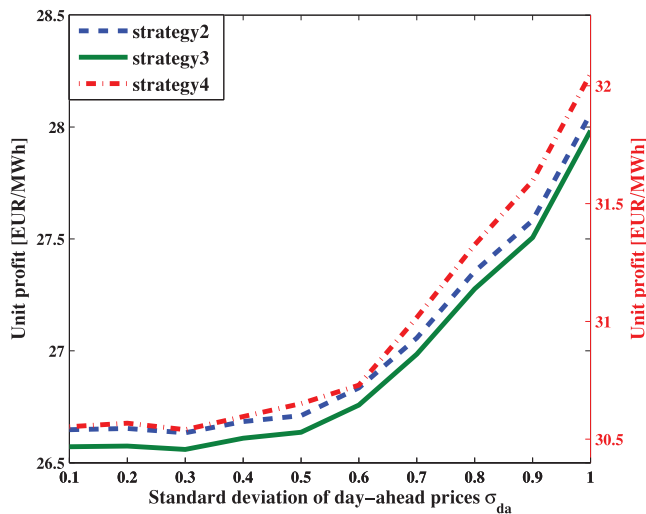


Fig. 5. Influence of day-ahead price forecast error on the unit profit. (double y-axis is used. Results of Strategy 2 and 3 read from the left axis while that of Strategy 4 reads from the right one. It is the same for Fig. 6).

Next, we analyze the impact of day-ahead and balancing prices uncertainty, and temporal correlation of wind power generation on profit. As a large number of scenarios are generated simulating the uncertain parameters, the overall wind energy for each scenario relating with different parameters may not be the same. For the sake of fairness, the item *unit profit* proposed in [13] is used in this paper.

As shown in (26), σ_{da} and σ_{rt} can be set to adjust the variance of the prices at each time interval, namely $\sigma_{da}\tilde{\varepsilon} \sim N(0, \sigma_{da}^2)$ and $\sigma_{rt}\tilde{\varepsilon} \sim N(0, \sigma_{rt}^2)$. The uncertainty of prices goes up with the increase of σ_{da} , σ_{rt} . It should be noted that since the prices are constrained to be non-negative, the price expectation will increase with the variance.

It can be concluded from Figs. 5 and 6 that profits of all strategies go up with the increase of price (both day-ahead prices and real-time prices) forecasting variance. Furthermore, by comparing these two figures one can find that Strategy 4 is more sensitive to the real-time prices.

From Fig. 5 we can see that the expected profits of different strategies have similar increase (1.5 EUR/MWh) when the uncertainty of day-ahead prices goes up. The reason is that the day-ahead bidding is determined and submitted before the day-ahead prices clearance, and day-ahead prices only affect the profit in the day-ahead market. Consequently, different strategies have similar increase of profit. When it comes to the balancing prices,

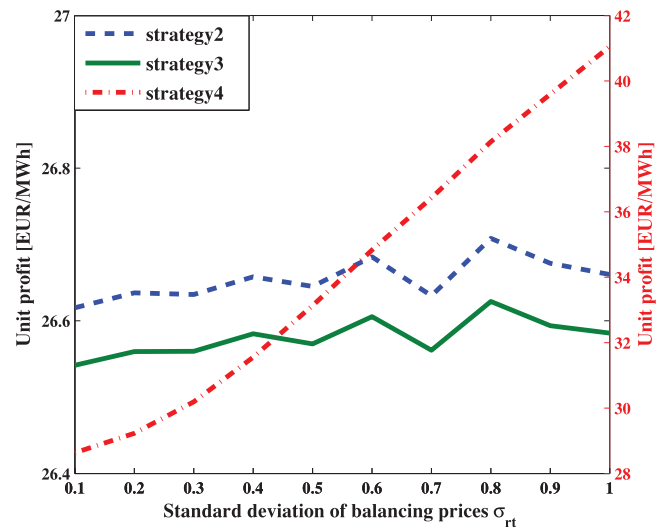


Fig. 6. Influence of balancing price forecast error on the unit profit.

TABLE III
IMPACT OF TEMPORAL CORRELATION OF WIND POWER
GENERATION ON THE VALUE OF ESS

ρ	-1	-0.8	-0.6	-0.4	-0.2	0
Unit advantage [EUR/MWh]	3.917	3.905	3.909	3.910	3.90	3.911
ρ	0.2	0.4	0.6	0.8	1.0	
Unit advantage [EUR/MWh]	3.918	3.897	3.913	3.892	3.923	

as Strategy 4 can effectively react to the real-time information, the occasional peak prices can be fully utilized to enhance the profit. On the contrary, other strategies neglect the price fluctuations, and take charging and discharging actions only depending on the wind power generation. So the joint generation is unrelated with the balancing prices, thus resulting in the profit less sensitive to the balancing prices.

The influence of temporal correlation of wind power is studied. It can be observed from Fig. 2 that Strategy 2 and 3 have very close profit distribution, Strategy 2 is chosen as the representative to compare with Strategy 4. Another motivation of this choice is that it is the best strategy where wind farm works alone. Consequently the advantage of Strategy 4 over 2 reveals the value of ESS in the wind farm participating electricity markets.

Table III shows that the increased profit brought by per MWh of wind energy through the proposed strategy (notated as unit advantage) remains steady with the increase of temporal correlation of wind power generation. This can be explained by that as the linear decision rules consider not only wind power but also day-ahead and balancing prices, the ESS can leave proper energy space to charge at lower prices or discharge at higher prices in the future, instead of only compensating for the wind power output deviations of current time interval. Consequently, the temporal correlation of wind power does not have much impact on the strategy. In other words, the ESS has guaranteed value cooperating with a WF using our proposed strategy.

Finally, we investigated the influence of the capacity and the initial residual energy of ESS on the daily profit of WF-ESS systems. From Fig. 7 one can see that both the expected value

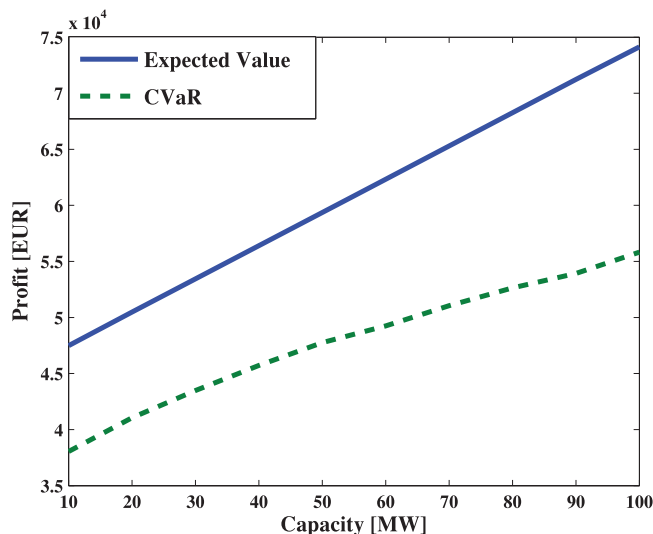


Fig. 7. Influence of the ESS capacity on the profit.

TABLE IV
IMPACT OF INITIAL RESIDUAL ENERGY OF ESS ON THE PROFIT

x_0 [MWh]	5	10	15	20	25
E [kEUR]	47.39	47.42	47.45	47.47	47.49
CVaR [kEUR]	38.05	38.08	38.06	38.04	38.05
x_0 [MWh]	30	35	40	45	50
E [kEUR]	47.49	47.47	47.44	47.38	47.31
CVaR [kEUR]	38.05	38.06	37.98	37.97	37.94

and the CVaR go up almost linearly with the increase of the capacity of ESS. It is natural because larger ESS implies more arbitrage capability of the WF-ESS system. As we do not study the optimal sizing problem, the investment cost of the ESS is not considered. It is also interesting that the daily profit of WF-ESS is not sensitive to the initial residual energy in ESS (shown in Table IV). This results from the introduction of term *energy value* in the objective function, which helps counteract the influence of daily energy deviation on the profit as expected.

V. CONCLUSION

This paper proposed and evaluated an integrated strategy for WF-ESS to optimally define offers as a price taker in day-ahead markets and operation policy at the balancing stage, based on linear decision rules. The strategy was modelled as a stochastic optimization problem taking uncertainty of market prices and wind power generation into account. The concept of energy value was additionally introduced to consider the value of the residual energy of ESS in the objective function. The objective function controls the balance between expected profit and risk aversion.

Case studies based on realistic data compared unit profits of different strategies, and showed substantial advantages of the proposed one (up to 12%) over other existing offering and operation strategies. Sensitivity analyses illustrated that the strategy can make better use of balancing price information. This indicates that the advantage of the proposed strategy would be more prominent in case of more uncertain and dynamic prices. Besides these nice features of our approach, it is also robust to

temporal correlation in wind power generation and the initial residual energy in the storage system. Furthermore, the Pareto efficient frontier was obtained to illustrate that the WF-ESS could tune its strategy based on risk preferences and then make a trade-off between the expected profit and risk.

Further work should relax the price-taker assumption and focus on price-maker strategies of WF-ESS. Other approaches to the design of integrated strategies should also be investigated, e.g., ones in a multi-stage stochastic programming framework. Meanwhile, since renewable energy generation sources and energy storage within a portfolio may certainly be distributed, the integrated offering strategy proposed here may be extended to a case with network constraints, and in a distributed optimization framework.

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REFERENCES

- [1] C. Wan, Z. Xu, P. Pinson, Z. Dong, and K. Wong, "Optimal prediction intervals of wind power generation," *IEEE Trans. Power Syst.* vol. 29, no. 3, pp. 1166–1174, Aug. 2013.
- [2] C. J. Dent, J. W. Bialek, and B. F. Hobbs, "Opportunity cost bidding by wind generators in forward markets: Analytical results," *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1600–1608, Aug. 2011.
- [3] L. Baringo and A. J. Conejo, "Strategic offering for a wind power producer," *IEEE Trans. Power Syst.* vol. 28, no. 4, pp. 4645–4654, Nov. 2013.
- [4] M. Zugno, T. Jönsson, and P. Pinson, "Trading wind energy on the basis of probabilistic forecasts both of wind generation and of market quantities," *Wind Energy*, vol. 16, no. 6, pp. 909–926, 2013.
- [5] J. García-González, R. M. R. de la Muela, L. M. Santos, and A. M. Gonzalez, "Stochastic joint optimization of wind generation and pumped-storage units in an electricity market," *IEEE Trans. Power Syst.* vol. 23, no. 2, pp. 460–468, May 2008.
- [6] H. Ding, Z. Hu, and Y. Song, "Rolling optimization of wind farm and energy storage system in electricity markets," *IEEE Trans. Power Syst.* vol. 30, no. 5, pp. 2676–2684, Sep. 2015.
- [7] H. Bludszweit and J. A. Dominguez-Navarro, "A probabilistic method for energy storage sizing based on wind power forecast uncertainty," *IEEE Trans. Power Syst.* vol. 26, no. 3, pp. 1651–1658, Aug. 2011.
- [8] Y. Yuan, Q. Li, and W. Wang, "Optimal operation strategy of energy storage unit in wind power integration based on stochastic programming," *IET Renew. Power Gener.* vol. 5, no. 2, pp. 194–201, May 2011.
- [9] M.-S. Lu, C.-L. Chang, W.-J. Lee, and L. Wang, "Combining the wind power generation system with energy storage equipment," *IEEE Trans. Ind. Appl.* vol. 45, no. 6, pp. 2109–2115, Sep. 2009.
- [10] J. Taylor, D. S. Callaway, and K. Poolla, "Competitive energy storage in the presence of renewables," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 985–996, May 2013.
- [11] E. D. Castronuovo, J. Usaola, R. Bessa, M. Matos, I. C. Costa, L. Bremermann, J. Lugaro, and G. Kariniotakis, "An integrated approach for optimal coordination of wind power and hydro pumping storage," *Wind Energy*, vol. 17, no. 6, pp. 829–852, Jun. 2014.
- [12] E. Bitar, R. Rajagopal, P. Kharagonekar, and K. Poolla, "The role of co-located storage for wind power producers in conventional electricity markets," in *Proc. 2011 Amer. Control Conf.*, 2011, pp. 3886–3891.
- [13] H. Ding, P. Pinson, Z. Hu, and Y. Song, "Integrated bidding and operating strategies for wind-storage systems," *IEEE Trans. Sustain. Energy*, vol. 7, no. 1, pp. 163–172, Jan. 2016.
- [14] I. Grønvik, A. Hadziomerovic, N. Ingvaldstad, R. Egging, and S.-E. Fleten, "Feasibility of linear decision rules for hydropower scheduling," in *Proc. 2014 IEEE Int. Conf. Probabilistic Methods Appl. to Power Syst.*, 2014, pp. 1–6.

- [15] X. Chen, M. Sim, P. Sun, and J. Zhang, "A linear decision-based approximation approach to stochastic programming," *Oper. Res.*, vol. 56, no. 2, pp. 344–357, 2008.
- [16] J. Warrington, P. Goulart, S. Mariéthoz, and M. Morari, "Policy-based reserves for power systems," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4427–4437, Nov. 2013.
- [17] M. Zugno, J. M. Morales, and H. Madsen, "Robust management of combined heat and power systems via linear decision rules," in *Proc. 2014 IEEE Int. Energy Conf.*, 2014, pp. 479–486.
- [18] J. Garcia-Gonzalez, A. San Roque, F. Campos, and J. Villar, "Connecting the intraday energy and reserve markets by an optimal redispatch," *IEEE Trans. Power Syst.* vol. 22, no. 4, pp. 2220–2231, Nov. 2007.
- [19] A. M. Jafari, H. Zareipour, A. Schellenberg, and N. Amjadi, "The value of intra-day markets in power systems with high wind power penetration," *IEEE Trans. Power Syst.* vol. 29, no. 3, pp. 1121–1132, May 2014.
- [20] J. M. Morales, A. J. Conejo, H. Madsen, P. Pinson, and M. Zugno, *Integrating Renewables in Electricity Markets—Operational Problems*. New York, NY, USA: Springer, 2014.
- [21] R. T. Rockafellar and S. Uryasev, "Optimization of conditional value-at-risk," *J. Risk*, vol. 2, pp. 21–42, 2000.
- [22] P. Krokmahl, J. Palmquist, and S. Uryasev, "Portfolio optimization with conditional value at risk objective and constraints," *J. Risk*, vol. 4, pp. 43–68, 2002.
- [23] S. Uryasev, "Condicionnal value-at-risk: Optimization algorithms and applications," *Financ. Eng. News*, vol. 14, pp. 3–8, 2000.
- [24] H. Ding, Z. Hu, and Y. Song, "Value of the energy storage system in an electric bus fast charging station," *Appl. Energy*, vol. 157, pp. 630–639, 2015.
- [25] Energinet, Download of Market Data [Online]. Available: <http://energinet.dk/EN/EI/Engrosmarked/Udtraek-af-markedsdata/Sider/default.aspx>
- [26] P. Pinson, "Wind energy: Forecasting challenges for its operational management," *Statist. Sci.* vol. 28, no. 4, pp. 564–585, Nov. 2013.
- [27] W. A. Bukhsh, C. Zhang, and P. Pinson, "A multiperiod OPF model under renewable generation uncertainty and demand side flexibility," *IEEE Trans. Smart Grid*, accepted for publication.
- [28] W. A. Bukhsh, 2014, Data for Stochastic Multiperiod Optimal Power Flow Problem [Online]. Available: <https://sites.google.com/site/datas-mopf/intro>
- [29] E. K. Aasgård, G. S. Andersen, S. E. Fleten, and D. Haugstvedt, "Evaluating a stochastic-programming-based bidding model for a multireservoir system," *IEEE Trans. Power Syst.*, vol. 29, no. 4, pp. 1748–1757, Jul. 2014.



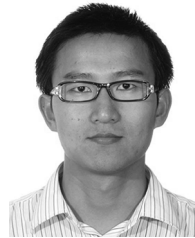
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