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Research Article

Optimal Offering and Operating Strategies for Wind-Storage System Participating in Spot Electricity Markets with Progressive Stochastic-Robust Hybrid Optimization Model Series

Yuwei Wang,[1] **Huiru Zhao**,[2] **and Peng Li**[3]

[1]*Department of Economic Management, North China Electric Power University, Baoding 071003, China*
[2]*School of Economics and Management, North China Electric Power University, Beijing 102206, China*
[3]*State Grid Henan Economic Research Institute, Zhengzhou, 450052, China*

Correspondence should be addressed to Yuwei Wang; wangyuwei2010@126.com

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With the increase of wind power installed capacity and the development of energy storage technologies, it is gradually accepted that integrating wind farms with energy storage devices to participate in spot electricity market (EM) is a promising way for improving wind power uncertainty accommodation and bringing considerable profit. Hence, research on reasonable offering and operating strategies for integrated wind farm-energy storage system (WF-ESS) under spot EM circumstances has important theoretical and practical significance. In this paper, a newly progressive stochastic-robust hybrid optimization model series is proposed for yielding such strategies. In the day-ahead stage, day-ahead and balancing prices uncertainties are formulated by applying joint stochastic scenarios, and real-time available wind power uncertainties are modeled by using the seasonal auto-regression (AR) based dynamic uncertainty set. Then, the first model of this model series is established and utilized for cooptimizing both the day-ahead offering and nominal real-time operating strategies. In the balancing stages, wind power uncertainty set and balancing prices stochastic scenarios are dynamically updated with the newly realized data. Then, each model from the remaining of this model series is established and utilized period by period for obtaining the optimal balancing/real-time offering/operating strategies adjusted from the nominal ones. Robust optimization (RO) in this progressive framework makes the operation of WF-ESS dynamically accommodate wind power uncertainties while maintaining relatively low computational complexity. Stochastic optimization (SO) in this progressive framework makes the WF-ESS avoid pursuing profit maximization strictly under the worst-case scenarios of prices uncertainties. Moreover, by adding a risk-aversion term in form of conditional value at risk (CVaR) into the objective functions of this model series, the optimization models additionally provide flexibility in reaching a trade-off between profit maximization and risk management. Simulation and profit comparisons with other existing methods validate the scientificity, feasibility, and effectiveness of applying our proposed model series.

1. Introduction

Nowadays, wind power has experienced a dramatic increase of installed capacity [1]. Participating in spot electricity markets (EMs) is considered by many researchers as a promising way for integrating wind power into power system [1, 2]. Owning to its unpredictable and stochastic natures, other controllable generators or flexible demand resources must be redispatched by system operator for balancing the deviations of wind farms' (WFs) real-time power outputs from their aforehand scheduled ones, which causes substantial balancing costs [3]. Moreover, WFs should suffer financial loss for their power output deviations because they should buy or sell up-/downregulations in balancing market. Fortunately, with the development of energy storage and newly energy conversion technologies such as batteries [4], flywheels [5], hydro pumped storage [6], and fuel cell facilities [7, 8], it is gradually accepted that WFs should be integrated into hybrid

energy systems containing energy storage and/or newly energy conversion sources [9]. Taking the integrated wind farm-energy storage system (WF-ESS) as representative, due to the flexible charging and discharging capabilities of energy storage, WF-ESS has two potentials when participating in spot EMs. One is to internally accommodate wind power uncertainties (power compensation), and the other is to strategically offer its integrated power outputs according to forecasted price differences at different market stages and time units (arbitrage). However, exploiting the above potentials urgently requires reasonable offering and operating strategies. Therefore, studies on such strategies for an integrated WF-ESS participating in spot EMs have received more and more attentions from both the industry and academia.

It should be noted that spot EM clearing prices and real-time available wind power outputs are usually uncertain for a WF-ESS (or other hybrid energy systems integrated with WF, etc.) at the time to make its offering and/or operating decisions. Reference [10] proposed an optimal operation model for a fuel cell-wind turbine hybrid system by applying a new extremum seeking control algorithm. Authors in [11] investigated the operation of a photovoltaic-wind-fuel cell hybrid system based on the simulated method performed in the HOMER software, in which the technical and economic feasibilities of this hybrid system have been numerically validated. However, uncertainties are not mathematically considered in [10, 11]. In [12], a two-stage optimization approach was applied for day-ahead and real-time scheduling of a hybrid power system consisting of WFs and batteries, etc. In the day-ahead stage, genetic algorithm based scheduling strategy was proposed for obtaining the "best-fit" day-ahead schedules. In the real-time stage, a probabilistic optimal power flow model was constructed for accommodating wind power uncertainties based on wind power stochastic scenarios. Authors in [13] established a mixed integer linear stochastic optimization (SO) model for cooptimizing offering strategies of wind-thermal-pumped storage system in energy and regulation markets, where uncertainties include wind power, day-ahead clearing prices, and regulation deployments. Reference [14] presented a multistage SO model to find the optimal offering and operating strategy of a WF-ESS in the day-ahead, intraday, and secondary reserve markets while taking into account uncertainties in wind power generation and EM clearing prices. Reference [15] added a risk-aversion term in form of conditional value at risk (CVaR) in SO based model to additionally provide flexibility in finding a trade-off between profit maximization and risk management of WF-ESS operation under EM circumstances. In [16], machine learning was leveraged to define scenarios; then a two-stage convex SO model was formulated for WF-ESS to participate in pool market. Reference [17] introduced the demand response (DR) for integration with WF-ESS, and a SO based day-ahead offering decision-making model was proposed for this DR-WF-ESS. Reference [18] integrated wind turbines, natural gas unit, energy storage, etc. as an energy hub (EH) and proposed a SO based day-ahead bidding decision-making model for this EH considering clearing prices and wind power uncertainties. Reference [19] proposed a multiobjective SO based dispatch model for optimizing total system losses and operating cost for a wind, PV, and storage integrated hybrid energy system. Via using SO related approaches, joint energy and reserve market clearing mechanisms were presented in [20–22] with the consideration of renewable power uncertainties.

In addition to the SO based approaches, robust optimization (RO) methods are also applied by many researchers in obtaining the optimal offering and/or operating strategies for a WF-ESS (or other hybrid energy systems integrated with WF and ESS, etc.). Reference [23] proposed an adaptive robust self-scheduling model for a WF paired with a compressed air energy storage system to participate in the day-ahead EM, given the inherent uncertainties in EM clearing prices and available wind power output. In [24], a robust security-constrained unit commitment model is established for a wind–thermal–hydro system with energy storage, in which uncertainty sets are used to characterize the uncertainty of wind power outputs. Authors in [25] developed a RO based model predictive control (RMPC) scheme to determine the optimal offering and operating strategies of a WF-ESS participating in multistage spot EMs, given the uncertainty set in spot EM prices. Considering multiple uncertainties such as wind power, a multi-interval-uncertainty constrained RO model was established in [26] to yield the optimal day-ahead offering and dispatching strategy for an AC/DC micro-grid containing wind turbines, energy storage devices, etc. Reference [27] aggregated the wind and photovoltaic generation, thermal and electro-chemical storage devices at the residential level, and proposed a RO based model for this aggregator to participate in day-ahead market. Reference [28] integrated wind turbines, electrical energy storage, etc. into a community energy system (ICES) and proposed a RO based day-ahead scheduling model for this ICES in a joint energy and ancillary service market. Combined with an interval forecasting method for depicting wind power and clearing prices uncertainties, a RO based model was proposed in [29] to obtain the optimal offering and operating strategies of a WF-ESS participating in day-ahead EM.

In summary, SO and RO are popular approaches to address WF-ESS's offering and operating decision-making problems nowadays. In those SO related methodologies ([13–22], etc.), uncertainties are forecasted and formulated by applying multiple stochastic scenarios. In those RO related methodologies ([23–29], etc.), uncertainties are forecasted and formulated by using interval based uncertainty set. WF-ESS's potentials for power compensation and arbitrage can be exploited to some extent due to the market fluctuations and power intermittences reflected in corresponding scenarios and uncertainty sets. However, with regard to the SO models, the computational complexity increases significantly with the introduction of multiple stochastic scenarios which make the number of WF-ESS's operational constraints increase accordingly. With regard to the RO models, although the computational complexity is relatively low due to the actual consideration of the "worst point" in uncertainty set affecting WF-ESS's profit, it often results in over conservativeness (obtained offering and/or operating strategies with relatively low economic efficiency) because the "good opportunities" in uncertainty set for bringing higher profits are ignored. More

Table 1: Presentations for the urgent competitive characteristics of the reviewed researches.

Approaches	Representative literature	Main features	Shortcomings
Deterministic optimization models	[10, 11]	Easy to understand and feasible for testing system performance from both the technical and economic perspectives etc	Uncertainties are not mathematically considered and modeled.
SO based models	[12–22]	Describing uncertainties of wind power and/or prices by using stochastic scenarios, pursuing the maximization of expected profit and/or profit CVaR while considering operational constraint under each stochastic scenario etc.	Requiring considerable computational effort, discretized wind power scenarios cannot guarantee the satisfaction of a WF-ESS's obtained offering and/or operating strategies for all operational constraints etc.
RO based models	[23–29]	Describing uncertainties of wind power and/or prices by using continuous uncertainty set, pursuing the maximization of profit under the worst-case point in the uncertainty set, Requiring low computational effort, and maintaining robustness of resisting uncertainties etc.	Often resulting in over conservativeness (severely sacrifice the optimality of the obtained offering and/or operating strategies for a WF-ESS) etc.

intuitive and specific presentations for the urgent competitive characteristics of the above reviewed researches are reflected in Table 1.

Moreover, as mentioned in [30, 31], another critical factor impacting the performance of a general RO based model is the structure of the uncertainty set. According to the definition and classification standards in [31], uncertainty sets proposed in [23–29] can be regarded as static ones which usually result in the overly conservative solutions. That is because in a static uncertainty set, on one hand, value interval of every uncertain parameter within every time unit can hardly be dynamically updated as time goes by and, on the other hand, correlations among different time units and/or different uncertain parameters are not systematically represented [30].

Since both the SO and RO methods have their own disadvantages mentioned above, a natural idea is that it may be possible to combine SO with RO to make the hybrid method further improve the optimization effect. Moreover, authors in [30] have proposed that real-time available wind or solar power outputs present significant temporal correlations. Hence, uncertainties of real-time available wind power outputs forecasted by using newly updated information would gradually weaken as time approaching. That is to say progressively making WF-ESS's offering and operating decisions in multistage spot EMs can dynamically take advantage of newly added data so as to make the WF-ESS pursue more profit.

Therefore, in this paper, by taking a "price taker" WF-ESS participating in day-ahead and balancing EMs [15] as representative, a newly progressive stochastic-robust hybrid optimization model series is proposed to obtain the WF-ESS's offering and operating strategies in multistage spot EMs. Different from most existed models, the main *novelties* of this paper can be summarized as follows.

(1) Every model in our model series has the mathematical characteristics of stochastic-robust hybrid optimization structure. SO is mainly reflected in that the objective function (pursuing profit maximization) is constructed according to the joint stochastic scenarios of day-ahead and/or balancing clearing prices; RO is mainly reflected in that all constraints must be satisfied when the "worst point" of wind power uncertainties affecting the operation of WF-ESS occurs.

(2) In every model of our model series, since all operational constraints of WF-ESS are not directly affected by price scenarios, the computational complexity of our models is greatly reduced compared to the SO based models.

(3) In every model of our model series, since all operational constraints of WF-ESS must be satisfied under the "worst point" of wind power uncertainties, the internal power compensation potential of WF-ESS is fully exploited.

(4) In every model of our model series, since the objective function is not directly affected by wind power uncertainties, WF-ESS does not need to make offering and/or operating decisions when the "worst point" of wind power uncertainties affecting WF-ESS's profit occurs, which greatly reduces the conservativeness of decision-making compared to the RO based models.

(5) In every model of our model series, since the objective function only contains the price stochastic parameters, the arbitrage potential of WF-ESS to pursue profit maximization based on forecasted price signals from multistage spot EMs is fully reflected.

(6) Our proposed model series can be divided into two progressive parts. The first part models the WF-ESS's day-ahead offering decision-making problem, and the second part consists of the balancing/real-time offering/operating decision-making models corresponding to balancing market stages throughout

the whole delivery day. By progressively implementing our model series, both of the price stochastic scenarios and dynamic wind power uncertainty set are dynamically updated due to the new data, thus reducing the uncertainties of price and wind power and their impact on decision-makings.

(7) By adding a risk-aversion term in form of conditional value at risk (CVaR) into the objective functions of this model series, the optimization models additionally provide flexibility in reaching a trade-off between profit maximization and risk management.

Accordingly, in addition to directly provide an efficient and feasible decision-making tool for WF-ESS operating and participating in spot EM circumstances, the contributions of this paper are mainly reflected in those abovementioned novelties which further expand the operation optimization theories of hybrid energy systems.

The rest of this paper is organized as follows: in Section 2, WF-ESS's offering and operating process based on our proposed progressive optimization frame work is concretely introduced. Section 3 formulates the day-ahead offering decision-making model and balancing/real-time offering/operating decision-making models for WF-ESS through using our proposed progressive stochastic-robust hybrid optimization model series. Simulation and model comparisons are implemented in Section 4 for verifying the feasibility and rationality of our method, and Section 5 concludes the paper.

2. WF-ESS's Offering and Operating Process Based on Progressive Decision-Making Framework

2.1. Imbalance Management in Electricity Market. Generally speaking, due to the small trading amount in intraday markets, deregulated spot EMs can be typically assumed as consisting of day-ahead and balancing market stages [15]. Participants are permitted to bid for their generation schedules of the whole time horizon of the next day (delivery day) in the day-ahead EM which is cleared 10 to 12 hours prior to the start of the delivery day. If a stochastic generator is integrated in a participant, real-time deviations from this participant's day-ahead scheduled power outputs are often inevitable and must be settled in the balancing market. For example, the WF-ESS should buy or sell up-/downregulation services for its negative or positive deviations, respectively, in balancing markets if the WF's real-time power deviations cannot be fully compensated by ESS. In some EMs like Dutch APX, balancing prices for up- and downregulations are the same, which are known as the one-price balancing settlement. Furthermore, balancing settlements which consist of different up- and downregulation prices are called two-price ones such as that in Nord Pool and the Iberian markets. In our paper, we propose the day-ahead offering and balancing/real-time offering/operating decision-making model series based on the one-price balancing settlement for a "price taker" WF-ESS while the probabilities for WF-ESS to provide ancillary services are neglected. Moreover, our proposed model series can be easily extended to the case of two-price balancing settlement.

2.2. Progressive Decision-Making Framework for Offering and Operating Process. Taking one day for example, it is assumed that the whole time horizon for a delivery day can be discretized into T time units (e.g., 24 time units with 1 hour for the duration of each time unit). As mentioned in [32], balancing markets are single-period markets as they take place just minutes before actual energy delivery. Accordingly, there are one day-ahead market and T balancing markets for one delivery day, with one balancing market for each imbalance management corresponding to one time unit. With time proceeding, information for clearing prices and available wind power outputs can be progressively updated period by period, which are helpful for dynamically improving the WF-ESS's total profit obtained from participating in both the day-ahead and balancing markets. Hence, in our paper, a progressive decision-making framework is proposed for WF-ESS to determine, dynamically, the optimal day-ahead/balancing offering and real-time operating strategies in spot EMs. Correspondingly, a series of optimization models are progressively established and solved. By solving each optimization model, the solutions in an adjustable finite predictive horizon are codetermined. However, only part of these solutions is implemented and the remaining ones are discarded or delivered to the rest models for further adjustment. Figure 1 depicts the decision procedure for a "price taker" WF-ESS participating in both day-ahead and balancing markets based on our proposed progressive decision-making framework.

From Figure 1, the following can be seen.

(1) There are one decision-making model for day-ahead stage and T decision-making models for balancing stages. Uncertainties $\{\widetilde{P}_t^{W,av}\}_{t=1}^T$ and $\{\widetilde{\lambda}_t^{da}\}_{t=1}^T$, $\{\widetilde{\lambda}_t^{re}\}_{t=1}^T$ forecasted right before the day-ahead stage are fed to the day-ahead decision-making model for obtaining the optimal day-ahead offering quantities (offering strategies, $\{P_t^{da}\}_{t=1}^T$) and the nominal real-time operating powers ($\{\widehat{P}_t^W\}_{t=1}^T, \{\widehat{P}_t^C\}_{t=1}^T, \{\widehat{P}_t^D\}_{t=1}^T$). Day-ahead decision-making model is established for the whole time horizon of the delivery day. Moreover, only $\{P_t^{da}\}_{t=1}^T$ are submitted in the day-ahead market, and $\{\widehat{P}_t^W\}_{t=1}^T, \{\widehat{P}_t^C\}_{t=1}^T, \{\widehat{P}_t^D\}_{t=1}^T$ are delivered to the balancing/real-time decision-making models for power adjustments.

(2) Each of these T balancing/real-time decision-making models is implemented for participating in the corresponding balancing market in the delivery day. Taking the nth ($1 \leq n \leq T$) balancing/real-time model for example, input information for this model consists of $\{\widehat{P}_t^W\}_{t=n}^T, \{\widehat{P}_t^C\}_{t=n}^T, \{\widehat{P}_t^D\}_{t=n}^T$, $P_n^{W,av}$, realization of SoC_{n-1} and the latest updated uncertainties $\{\widetilde{P}_t^{W,av}\}_{t=n+1}^T, \{\widetilde{\lambda}_t^{re}\}_{t=n}^T$. It is assumed that real-time available wind power output forecasted few minutes

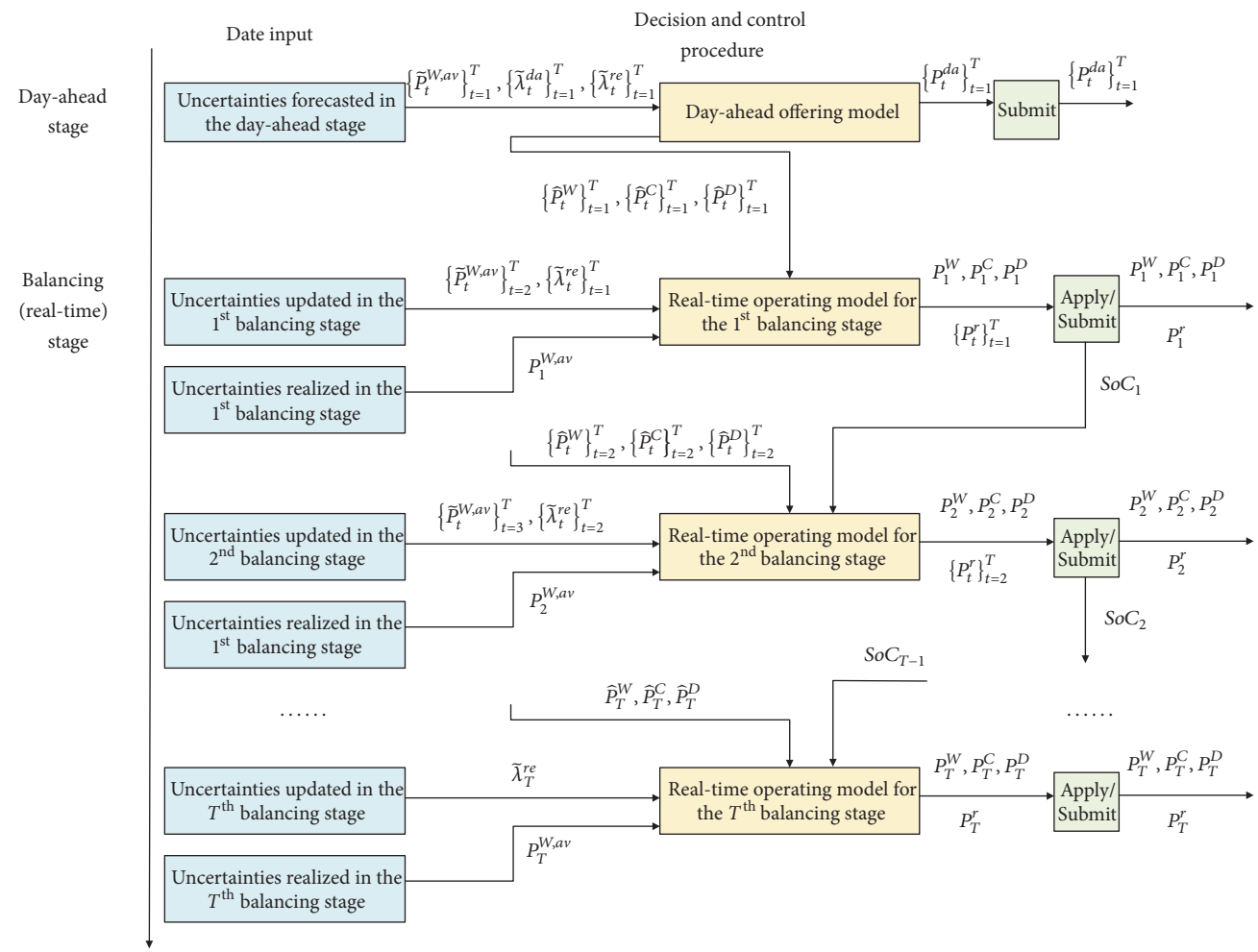

Figure 1: Decision procedure for a "price taker" WF-ESS participating in both day-ahead and balancing markets based on progressive decision-making framework.

before its actual delivery can be deemed as accurate information [26]. Then, the outputs of the nth balancing/real-time model contain $\{P_t^W, P_t^C, P_t^D\}_{t=n}^T$ and $\{P_t^r\}_{t=n}^T$. However, among those outputs, what the WF-ESS actually implements in the nth balancing stage are only $\boldsymbol{P}_n = [P_n^W, P_n^C, P_n^D]^{\mathrm{T}}$ and P_n^r according to the basic rules of our proposed progressive decision-making framework. The relationship between the actual and nominal operating powers of the WF-ESS for time unit n can be formulated as

$$\boldsymbol{P}_n = \begin{bmatrix} P_n^W \\ P_n^C \\ P_n^D \end{bmatrix} = \begin{bmatrix} \widehat{P}_n^W \\ \widehat{P}_n^C \\ \widehat{P}_n^D \end{bmatrix} + \begin{bmatrix} \Delta P_n^W \\ \Delta P_n^C \\ \Delta P_n^D \end{bmatrix} = \widehat{\boldsymbol{P}}_n + \Delta \boldsymbol{P}_n \tag{1}$$

where $\Delta \boldsymbol{P}_n = [\Delta P_n^W, \Delta P_n^C, \Delta P_n^D]^T$ represents the optimal power adjustment vector for time unit n. Actually, in the nth balancing/real-time model, determining the optimal actual real-time operating power vector $\boldsymbol{P}_n$ is equivalent to determining the optimal power adjustment vector $\Delta \boldsymbol{P}_n$.

(3) It should be noted that when the nth balancing/real-time model is executed, there actually exists a stationary mathematical relationship among P_n^r, P_n^{da} and $\boldsymbol{P}_n$, which can be formulated as

$$P_n^r = \boldsymbol{D}^T \boldsymbol{P}_n - P_n^{da} \tag{2}$$

where $\boldsymbol{D} = [1, -1, 1]^T$. Eq. (2) means if $\boldsymbol{D}^T \boldsymbol{P}_n > P_n^{da}$ (P_n^r is positive), WF-ESS should sell P_n^r MW upregulations in the nth balancing market; otherwise, WF-ESS should buy $-P_n^r$ MW downregulations in the nth balancing market.

3. WF-ESS's Offering and Operating Models Based on Progressive Stochastic-Robust Hybrid Optimization Method

3.1. Formulations for Uncertainties. According to [13–16], parameters in all operational constraints of a WF-ESS are irrelevant to day-ahead and balancing clearing prices, which means uncertainties of day-ahead and balancing clearing

prices would not cause violations of operational constraints for a specific combination of day-ahead/balancing offering ($\{P_t^{da}\}_{t=1}^T/\{P_t^r\}_{t=1}^T$) and real-time operating ($\{P_t^W, P_t^C, P_t^D\}_{t=1}^T$) strategies. That is to say, if using a number of joint stochastic scenarios to only represent uncertainties of day-ahead and balancing prices, there would be no increase in the number of WF-ESS's operational constraints. Hence, with respect to prices uncertainties, it is more feasible to apply the SO based methods for WF-ESS's offering and operating decision-making modeling than RO-based ones. On one hand, limited and constant number of operational constraints irrelevant to prices scenarios ensures low computational complexity. On the other hand, it often brings lower conservativeness for the solutions obtained from the expected-case optimization than those from the worst-case optimization. Contrarily, parameters in most operational constraints of a WF-ESS are actually related to real-time available wind power outputs. That is to say, if using a number of stochastic scenarios to represent uncertainties of real-time available wind power outputs, the number of WF-ESS's operational constraints would increase significantly. Hence, with respect to wind power uncertainties, it is more feasible to apply the RO-based methods for WF-ESS's offering and operating decision-making modeling than SO based ones due to the shortcomings for SO based models as mentioned in Section 1.

Therefore, we propose a stochastic-robust hybrid optimization method to construct both the day-ahead offering decision-making model and every balancing/real-time offering/operating one for WF-ESS. On one hand, joint stochastic scenarios are dynamically generated for formulating prices uncertainties, which make the expected-case optimization feasible in every decision-making model within our progressive model series. On the other hand, available wind power uncertainties are formulated as dynamic uncertainty set which can be easily updated period by period for the purpose of reducing the conservativeness of obtained strategies.

According to WF-ESS's decision procedure mentioned in Section 2.2, joint stochastic scenarios for day-ahead and balancing clearing prices are needed in the day-ahead model while joint stochastic scenarios for balancing clearing prices from time unit n to T are needed in the nth balancing/real-time model. Method for prices scenarios generation applied in our paper is the same as that in [15], which make the generated scenarios easily be dynamically updated via using newly realized prices data. The procedures for dynamically generating joint prices scenarios can be easily found in [15].

Moreover, according to [30], dynamic uncertainty set of real-time available wind power outputs can be formulated as (taking uncertainty set for the nth balancing stage for example)

$$\boldsymbol{U}_{W,n} = \left\{\widetilde{\boldsymbol{P}}_{W,av} = \left(\widetilde{P}_{n+1}^{W,av}, \widetilde{P}_{n+2}^{W,av}, \ldots, \widetilde{P}_{T}^{W,av}\right): \quad \exists \mu, \nu, \right. \tag{3a}$$

s.t.

$$\widetilde{P}_t^{W,av} = f_t + g_t\widetilde{\mu}_t, \quad \forall t = n+1, \ldots, T \tag{3b}$$

$$\widetilde{\mu}_t = \sum_{l=1}^{L} a_l\widetilde{\mu}_{t-l} + \delta\nu_t, \quad \forall t = n+1, \ldots, T \tag{3c}$$

$$\sum_{t=n+1}^{T} \left|\nu_t\right| \le \rho\left(\mathrm{T} - n\right), \quad 0 \le \rho \le 1 \tag{3d}$$

$$0 \le \widetilde{P}_t^{W,av} \le P_{\max}^W, \quad \forall t = n+1, \ldots, T\} \tag{3e}$$

where f_t and g_t account for deterministic seasonal components and ρ is equivalent to a budget parameter over periods. Eq. (3b) separates the residual component $\widetilde{\mu}_t$ from $\widetilde{P}_t^{W,av}$ through seasonal decomposition method [30]. Eq. (3c) is the key equation that represents a linear dynamic relationship involving the residual $\widetilde{\mu}_t$ at time unit t, residuals in earlier periods t-L to t-1, and an error term $\delta\nu_t$ [30]. L represents the relevant time lags. $\boldsymbol{a} = (a_1, \ldots, a_L)^T$ represents the autoregressive coefficient vector. δ represents the standard deviation of the white noise term $\delta\nu_t$, which means ν_t actually stands for a standard normal random variable. Hence, Eq. (3d) controls the size of the whole set via adjusting ρ's value; e.g. if ρ is set to 0, it means none of the uncertainties of ν_t ($t = n+1, \ldots, T$) is taken into account; if ρ is set to 1, it means all of the uncertainties of ν_t ($t = n+1, \ldots, T$) within $[-1, 1]$ are taken into account. Moreover, (3e) determines an upper bound $P_{\max}^W$ (e.g., installed capacity for the WF) on $\widetilde{P}_t^W$.

It should be noted that

(1) if the uncertainty set is forecasted and formulated in the day-ahead stage, then both $\widetilde{P}_t^{W,av}$ ($\forall t$) and $\widetilde{\mu}_t$ ($\forall t$) for the delivery day are unrealized; parameters f_t ($\forall t$), g_t ($\forall t$), $\boldsymbol{a} = (a_1, \ldots, a_L)^T$ and δ are estimated by using historical available wind power data realized up to the day-ahead stage;

(2) if the uncertainty set is forecasted and formulated in the balancing stage corresponding to time unit n, then both $\widetilde{P}_t^{W,av}$ ($t = 1, 2, \ldots, n$) and $\widetilde{\mu}_t$ ($t = 1, 2, \ldots, n$) for the delivery day are realized; parameters f_t ($t = n+1, n+2, \ldots, T$), g_t ($t = n+1, n+2, \ldots, T$), $\boldsymbol{a} = (a_1, \ldots, a_L)^T$ and δ can be estimated by using realized available wind power data up to the nth balancing stage, which is the fundamental of the proposed dynamic uncertainty set to be updated period by period.

3.2. Formulations for Day-Ahead Offering Decision-Making Model. As mentioned in Section 2.2, the optimal day-ahead offerings $\{P_t^{da}\}_{t=1}^T$ and nominal real-time operating powers $\{\widehat{P}_t^W\}_{t=1}^T$, $\{\widehat{P}_t^C\}_{t=1}^T$, $\{\widehat{P}_t^D\}_{t=1}^T$ throughout the whole time horizon of the delivery day are determined in the day-ahead stage for a "price taker" WF-ESS. Hence, under a given combination of $\{P_t^{da}\}_{t=1}^T$, $\{\widehat{P}_t^W\}_{t=1}^T$, $\{\widehat{P}_t^C\}_{t=1}^T$, and $\{\widehat{P}_t^D\}_{t=1}^T$, total profit for the WF-ESS participating in both the day-ahead and balancing markets can be formulated as

$$\widetilde{S} = \sum_{t=1}^{T} \left[\widetilde{\lambda}_{t,\omega_{da}}^{da} P_t^{da} + \widetilde{\lambda}_{t,\omega_{da}}^{re} \widehat{P}_t^r - C_W\widehat{P}_t^W - C_E\widehat{E}_t\right] \tag{4}$$

where $\widehat{P}_t^r$ ($\forall t$) represents the nominal balancing offering decision for buying ($\widehat{P}_t^r \le 0$)/selling ($\widehat{P}_t^r > 0$) up-/downregulations in the tth balancing market of the delivery

day, C_W and C_E represent cost parameters of WF and ESS (the degradation costs for ESS is ignored here), respectively. It is easy to tell from (4) that uncertainty of $\widetilde{S}$ is only related to prices uncertainties due to our introduction of nominal variables. Moreover, it should be noted that both $\widehat{P}_t^r$ and $\widehat{E}_t$ are by-products of $P_t^{da}\widehat{P}_t^W$, $\widehat{P}_t^C$, and $\widehat{P}_t^D$; their relationship can be formulated as

$$\widehat{P}_t^r = \boldsymbol{D}^T\widehat{\boldsymbol{P}}_t - P_t^{da}, \quad \forall t \tag{5}$$

$$\widehat{E}_t = E_0 + \sum_{j=1}^{t}\widehat{P}_j^C\eta_C\Delta t - \sum_{j=1}^{t}\left(\frac{\widehat{P}_j^D}{\eta_D}\right)\Delta t, \quad \forall t \tag{6}$$

where E_0 stands for the initial residual energy of the ESS and η_C and η_D are charging and discharging efficiencies of the ESS.

In the day-ahead stage, WF-ESS pursues the maximization of expected total profit while considering potential risk. Similar to [15], the risk is formulated by CVaR and is cooptimized with the expected total profit through linear combination. Moreover, owing to the introduction of nominal variables, WF-ESS's day-ahead offering decision-making problem can be formulated as the following stochastic-robust hybrid optimization model, which is the first model in our proposed progressive stochastic-robust hybrid optimization model series:

$$\max_{P_t^{da},\widehat{P}_t^r,\widehat{P}_t^W,\widehat{P}_t^C,\widehat{P}_t^D,\forall t} \quad \gamma \mathrm{E}\left(\widetilde{S}\right) + (1-\gamma)\,\mathrm{CVaR}_\alpha\left(\widetilde{S}\right) \tag{7a}$$

s.t.

Eq. (5)

$$0 \le \widehat{P}_t^W \le P_{\max}^W, \quad \forall t \tag{7b}$$

$$P_{\min}^C \le \widehat{P}_t^C \le P_{\max}^C, \quad \forall t \tag{7c}$$

$$P_{\min}^D \le \widehat{P}_t^D \le P_{\max}^D, \quad \forall t \tag{7d}$$

Eq. (6)

$$E_{\min} \le \widehat{E}_t \le E_{\max}, \quad \forall t \tag{7e}$$

$$\begin{aligned}
&\boldsymbol{P}_{ar} = \left(P_1^{da}, P_2^{da}, \ldots, P_T^{da}, \widehat{P}_1^r, \widehat{P}_2^r, \ldots, \widehat{P}_T^r, \widehat{P}_1^W, \widehat{P}_2^W, \ldots, \widehat{P}_T^W, \widehat{P}_1^C, \widehat{P}_2^C, \ldots, \widehat{P}_T^C, \widehat{P}_1^D, \widehat{P}_2^D, \ldots, \widehat{P}_T^D\right) \in \boldsymbol{\Omega}_{da} \\
&\boldsymbol{\Omega}_{da} := \{\boldsymbol{P}_{ar} : \forall \widetilde{\boldsymbol{P}}_{w,av} = \left(\widetilde{P}_1^{W,av}, \widetilde{P}_2^{W,av}, \ldots, \widetilde{P}_T^{W,av}\right) \in \boldsymbol{U}_{W,da}, \\
&\exists \Delta\boldsymbol{P}_{da} = \left(\Delta P_1^W, \Delta P_2^W, \ldots, \Delta P_T^W, \Delta P_1^C, \Delta P_2^C, \ldots, \Delta P_T^C, \Delta P_1^D, \Delta P_2^D, \ldots, \Delta P_T^D\right)
\end{aligned} \tag{7f}$$

such that

$$\begin{aligned}
&\widehat{P}_t^r = \boldsymbol{D}^T\left(\widehat{\boldsymbol{P}}_t + \Delta\boldsymbol{P}_{da,t}\right) - P_t^{da}, \\
&\Delta\boldsymbol{P}_{da,t} = \left[\Delta P_t^W, \Delta P_t^C, \Delta P_t^D\right]^T, \ \forall t
\end{aligned} \tag{7g}$$

$$0 \le \widehat{P}_t^W + \Delta P_t^W \le \widetilde{P}_t^{W,av}, \quad \forall t \tag{7h}$$

$$0 \le \widehat{P}_t^C + \Delta P_t^C \le P_{\max}^C, \quad \forall t \tag{7i}$$

$$0 \le \widehat{P}_t^D + \Delta P_t^D \le P_{\max}^D, \quad \forall t \tag{7j}$$

$$\begin{aligned}
E_t &= E_0 + \sum_{j=1}^{t}\left(\widehat{P}_j^C + \Delta P_j^C\right)\eta_C\Delta t \\
&\quad - \sum_{j=1}^{t}\left[\frac{\left(\widehat{P}_j^D + \Delta P_j^D\right)}{\eta_D}\right]\Delta t, \quad \forall t
\end{aligned} \tag{7k}$$

$$0 \le E_t \le E_{\max}, \quad \forall t\} \tag{7l}$$

where $P_{\max}^W$, $P_{\max}^C$, $P_{\max}^D$, and $E_{\max}$ are the technical maximum limits for WF's power output, ESS's charging and discharging powers, as well as ESS's residual energy; $P_{\min}^C$, $P_{\min}^D$, and $E_{\min}$ are the technical minimum limits for ESS's charging and discharging powers, as well as ESS's residual energy.

Eqs. (5)-(6) and (7b)-(7e) together represent the operational constraints of WF-ESS. The robust feasible region $\boldsymbol{\Omega}_{da}$ represented by (7f)-(7l) restricts the WF-ESS's decision $\boldsymbol{P}_{ar}$ made in the day-ahead stage so as to satisfy all operational constraints under any potential realization within $\boldsymbol{U}_{W,da}$ (uncertainty set forecasted in the day-ahead stage) by implementing existent corresponding adjustment $\Delta\boldsymbol{P}_{da}$.

Eq. (7a) indicates the objective function of the WF-ESS in the day-ahead stage, where $\mathrm{E}(\widetilde{S})$ stands for the expected value function of $\widetilde{S}$; $\mathrm{CVaR}_\alpha(\widetilde{S})$ represents the CVaR value function of $\widetilde{S}$ at confidence level of α. The objective function controls the trade-off between the expectation and CVaR with an exogenous parameter γ ($0 \le \gamma \le 1$), the increase of which makes the strategy more risk-neutral. Moreover, based on method proposed in [15] for CVaR linearization and according to our introduction of nominal variables, (7a) can be linearized by using day-ahead and balancing prices joint stochastic scenarios, and the linearized form of (7a) is presented as follows:

$$\begin{aligned}
&\max_{P_t^{da},\widehat{P}_t^r,\widehat{P}_t^W,\widehat{P}_t^C,\widehat{P}_t^D,\forall t} \\
&\quad \gamma \sum_{\omega_{da}\in\Theta_{da}} \rho_{\omega_{da}} \sum_{t=1}^{T}\left(\lambda_{t,\omega_{da}}^{da} P_t^{da}\right. \\
&\quad \left. + \lambda_{t,\omega_{da}}^{re}\widehat{P}_t^r - C_W\widehat{P}_t^W - C_E\widehat{E}_t\right)
\end{aligned}$$

$$+(1-\gamma)\left(\nu+\frac{1}{\alpha}\cdot\sum_{\omega_{da}\in\Theta_{da}}\rho_{\omega_{da}}z_{\omega_{da}}\right) \tag{8a}$$

$$\text{s.t.}\quad z_{\omega_{da}} \le \sum_{t=1}^{T}\left(\lambda_{t,\omega_{da}}^{da}P_t^{da} + \lambda_{t,\omega_{da}}^{re}\widehat{P}_t^r - C_W\widehat{P}_t^W - C_E\widehat{E}_t\right) - \nu,\quad \forall\omega_{da}\in\Theta_{da} \tag{8b}$$

$$z_{\omega_{da}} \le 0,\quad \forall\omega_{da}\in\Theta_{da} \tag{8c}$$

where ω_{da} and Θ_{da} are, respectively, the index and index set for day-ahead and balancing prices joint stochastic scenarios which are forecasted in the day-ahead stage; $\rho_{\omega_{da}}$ represents the probability of scenario ω_{da}; ν and $z_{\omega_{da}}$ ($\forall\omega_{da}\in\Theta_{da}$) are intermediate variables introduced in the linearization process of $\mathrm{CVaR}_\alpha(\widetilde{S})$, which are codetermined with $P_t^{da}, \widehat{P}_t^r, \widehat{P}_t^W, \widehat{P}_t^C, \widehat{P}_t^D$ ($\forall t$). Therefore, our proposed stochastic-robust hybrid optimization model for day-ahead offering decision-making can also be written as

Eq. (8a),

s.t. Eqs. (8b)-(8c),

Eqs. (5)-(6) and Eqs. (7b)-(7l).

3.3. Formulations for Balancing/Real-Time Offering/Operating Decision-Making Model. In the balancing stage, taking the nth balancing/real-time offering/operating decision-making model, for example, profits from day-ahead market and balancing markets before time unit n have already been obtained by WF-ESS. The remaining profits from the rest balancing markets of the delivery day should be maximized for the WF-ESS. Hence, similar to method in Section 3.3, WF-ESS's nth balancing/real-time offering/operating decision-making problem can be formulated as the following stochastic-robust hybrid optimization model, which is the n+1 th model in our proposed progressive stochastic-robust hybrid optimization model series:

$$\max_{\{P_t^r\}_{t=n}^T,\{P_t^W\}_{t=n}^T,\{P_t^C\}_{t=n}^T,\{P_t^D\}_{t=n}^T}\quad \gamma\sum_{\omega_{re,n}\in\Theta_{re,n}}\rho_{\omega_{re,n}}\left[\sum_{t=n}^{T}\lambda_{t,\omega_{re,n}}^{re}P_t^r - C_WP_t^W - C_EE_t\right] + (1-\gamma)\left(\nu+\frac{1}{\alpha}\sum_{\omega_{re,n}\in\Theta_{re,n}}\rho_{\omega_{re,n}}z_{\omega_{re,n}}\right) \tag{9a}$$

$$\text{s.t.}\quad z_{\omega_{re,n}} \le \left(\sum_{t=n}^{T}\lambda_{t,\omega_{re,n}}^{re}P_t^r - C_WP_t^W - C_EE_t\right) - \nu,\quad \forall\omega_{re,n}\in\Theta_{re,n} \tag{9b}$$

$$z_{\omega_{re,n}} \le 0,\quad \forall\omega_{re,n}\in\Theta_{re,n} \tag{9c}$$

$$\boldsymbol{P}_t = \widehat{\boldsymbol{P}}_t + \Delta\boldsymbol{P}_t,\quad t=n,n+1,\ldots,T \tag{9d}$$

$$P_t^r = \boldsymbol{D}^T\boldsymbol{P}_t - P_t^{da},\quad t=n,n+1,\ldots,T \tag{9e}$$

$$0 \le P_n^W \le P_n^{W,av} \tag{9f}$$

$$0 \le P_t^W \le P_{\max}^W,\quad t=n+1,n+2,\ldots,T \tag{9g}$$

$$P_{\min}^C \le P_t^C \le P_{\max}^C,\quad t=n,n+1,\ldots,T \tag{9h}$$

$$P_{\min}^D \le P_t^D \le P_{\max}^D,\quad t=n,n+1,\ldots,T \tag{9i}$$

$$E_t = E_{n-1} + \sum_{j=n}^{t}P_j^C\eta_C\Delta t - \sum_{j=n}^{t}\left(\frac{P_j^D}{\eta_D}\right)\Delta t,\quad t=n,n+1,\ldots,T \tag{9j}$$

$$0 \le E_t \le E_{\max},\quad t=n,n+1,\ldots,T \tag{9k}$$

$$\begin{aligned}
&\boldsymbol{P}_{re,n} = \left(P_n^r, P_{n+1}^r,\ldots,P_T^r, P_n^W, P_{n+1}^W,\ldots,P_T^W, P_n^C, P_{n+1}^C,\ldots,P_T^C, P_n^D, P_{n+1}^D,\ldots,P_T^D\right)\in\boldsymbol{\Omega}_{re,n}\\
&\boldsymbol{\Omega}_{re,n} := \left\{\boldsymbol{P}_{re,n} : \forall\widetilde{\boldsymbol{P}}_{W,av,n} = \left(\widetilde{P}_{n+1}^{W,av}, \widetilde{P}_{n+2}^{W,av},\ldots,\widetilde{P}_T^{W,av}\right)\in\boldsymbol{U}_{W,n},\right.\\
&\exists\Delta\boldsymbol{P}_{ba,n}\\
&= \left(\Delta P_{n,n+1}^W, \Delta P_{n,n+2}^W,\ldots,\Delta P_{n,T}^W, \Delta P_{n,n+1}^C, \Delta P_{n,n+2}^C,\ldots,\Delta P_{n,T}^C, \Delta P_{n,n+1}^D, \Delta P_{n,n+2}^D,\ldots,\Delta P_{n,T}^D\right)
\end{aligned} \tag{9l}$$

such that

$$P_t^r = \boldsymbol{D}^T\left(\boldsymbol{P}_t + \Delta\boldsymbol{P}_{n,t}\right) - P_t^{da},$$
$$\Delta\boldsymbol{P}_{n,t} = \left[\Delta P_{n,t}^W, \Delta P_{n,t}^C, \Delta P_{n,t}^D\right]^T, \quad t = n+1, n+2, \ldots, T \tag{9m}$$

$$0 \le P_t^W + \Delta P_{n,t}^W \le \widetilde{P}_t^{W,av}, \quad t = n+1, n+2, \ldots, T \tag{9n}$$

$$0 \le P_t^C + \Delta P_{n,t}^C \le P_{\max}^C, \quad t = n+1, n+2, \ldots, T \tag{9o}$$

$$0 \le P_t^D + \Delta P_{n,t}^D \le P_{\max}^D, \quad t = n+1, n+2, \ldots, T \tag{9p}$$

$$\begin{aligned} E_{n,t} &= E_n + \sum_{j=n}^{t}\left(P_j^C + \Delta P_{n,t}^C\right)\eta_C\Delta t \\ &\quad - \sum_{j=n}^{t}\left[\frac{\left(P_j^D + \Delta P_{n,t}^D\right)}{\eta_D}\right]\Delta t, \\ &\qquad t = n+1, n+2, \ldots, T \end{aligned} \tag{9q}$$

$$0 \le E_{n,t} \le E_{\max}, \quad t = n+1, n+2, \ldots, T\} \tag{9r}$$

where $\omega_{re,n}$ and $\Theta_{re,n}$ are, respectively, the index and index set for balancing prices joint stochastic scenarios which are forecasted in the nth balancing stage by using the latest updated prices information prior to time unit n; $\rho_{\omega_{re,n}}$ represents the probability of scenario $\omega_{re,n}$; ν and $z_{\omega_{re,n}}$ ($\forall\omega_{re,n} \in \Theta_{re,n}$) are intermediate variables introduced in the linearization process of CVaR. ν and $z_{\omega_{re,n}}$ ($\forall\omega_{re,n} \in \Theta_{re,n}$) are codetermined with $\{P_t^r\}_{t=n}^T, \{P_t^W\}_{t=n}^T, \{P_t^C\}_{t=n}^T, \{P_t^D\}_{t=n}^T$ (although $\{P_t^r\}_{t=n}^T, \{P_t^W\}_{t=n}^T, \{P_t^C\}_{t=n}^T, \{P_t^D\}_{t=n}^T$ are cogenerated in the nth balancing/real-time offering/operating decision-making model, only $P_n^r, P_n^W, P_n^C, P_n^D$ are actually implemented in the nth balancing stage).

In summary, no matter with respect to day-ahead or balancing stage, the general theoretical flowchart of our proposed stochastic-robust optimization methodology can be demonstrated as follows.

3.4. Model Reformulation. The basic idea of the above model proposed in Section 3.2 or 3.3 is to find a stochastic-robust solution which, on one hand, is immunized against any available wind power uncertainties within $\boldsymbol{U}_{W,da}$ or $\boldsymbol{U}_{W,t}$ ($\forall t$) and, on the other hand, maximizes a linear combination of expectation and CVaR of profit based on prices stochastic scenarios. However, both of those two models should be reformulated so as to facilitate model solving. Inspired by [33], column and constraint generation (C&CG) based method is used to reformulate and solve the above models. With respect to the day-ahead offering decision-making model proposed in Section 3.2, by using C&CG method for reformulating, its master problem (namely, MP1) and subproblem (namely, SP1) are established as follows:

(MP1) Eq. (8a)
s.t. Eqs. (8b)-(8c)
Eqs. (5)-(6) and Eqs. (7b)-(7e)

$$0 \le \widehat{P}_t^W + \Delta P_{t,k}^W \le \widetilde{P}_{t,k}^{W,av}, \quad \forall t, \ \forall k \in \boldsymbol{\kappa}_{da} \tag{10a}$$

$$0 \le \widehat{P}_t^C + \Delta P_{t,k}^C \le P_{\max}^C, \quad \forall t, \ \forall k \in \boldsymbol{\kappa}_{da} \tag{10b}$$

$$0 \le \widehat{P}_t^D + \Delta P_{t,k}^D \le P_{\max}^D, \quad \forall t, \ \forall k \in \boldsymbol{\kappa}_{da} \tag{10c}$$

$$\begin{aligned} E_{t,k} &= E_0 + \sum_{j=1}^{t}\left(\widehat{P}_j^C + \Delta P_{j,k}^C\right)\eta_C\Delta t \\ &\quad - \sum_{j=1}^{t}\left[\frac{\left(\widehat{P}_j^D + \Delta P_{j,k}^D\right)}{\eta_D}\right]\Delta t, \quad \forall t, \ \forall k \in \boldsymbol{\kappa}_{da} \end{aligned} \tag{10d}$$

$$0 \le E_{t,k} \le E_{\max}, \quad \forall t, \ \forall k \in \boldsymbol{\kappa}_{da} \tag{10e}$$

$$\text{(SP1)} \quad \Psi_{SP1} = \max_{\widetilde{\boldsymbol{P}}_{w,av} \in \boldsymbol{U}_{W,da}} \ \min_{\boldsymbol{o}^+, \boldsymbol{o}^-, \boldsymbol{P}^+, \boldsymbol{P}^-, \boldsymbol{q}^+, \boldsymbol{q}^-, \boldsymbol{s}^+, \boldsymbol{s}^-, \boldsymbol{u}^+, \boldsymbol{u}^-, \Delta\boldsymbol{P}_{da}} \sum_{t=1}^{T}\left(o_t^+ + o_t^- + p_t^+ + p_t^- + q_t^+ + q_t^- + s_t^+ + s_t^- + u_t^+ + u_t^-\right) \tag{11a}$$

$$\begin{aligned} &\text{s.t. } o_t^+ \ge 0, \quad \forall t, \\ &o_t^- \ge 0, \quad \forall t, \\ &p_t^+ \ge 0, \quad \forall t, \\ &p_t^- \ge 0, \quad \forall t, \\ &q_t^+ \ge 0, \quad \forall t, \\ &q_t^- \ge 0, \quad \forall t, \\ &s_t^+ \ge 0, \quad \forall t, \\ &s_t^- \ge 0, \quad \forall t, \\ &u_t^+ \ge 0, \quad \forall t, \\ &u_t^- \ge 0, \quad \forall t \end{aligned} \tag{11b}$$

$$\widehat{P}_t^r = \boldsymbol{D}^T\left(\widehat{\boldsymbol{P}}_t + \Delta\boldsymbol{P}_t\right) - P_t^{da}, \quad \forall t \tag{11c}$$

$$0 \le \widehat{P}_t^W + \Delta P_t^W + o_t^+ - o_t^- \le \widetilde{P}_t^{W,av}, \quad \forall t \tag{11d}$$

$$0 \le \widehat{P}_t^C + \Delta P_t^C + q_t^+ - q_t^- \le P_{\max}^C, \quad \forall t \tag{11e}$$

$$0 \le \widehat{P}_t^D + \Delta P_t^D + s_t^+ - s_t^- \le P_{\max}^D, \quad \forall t \tag{11f}$$

Eqs. (7l)

$$0 \le E_t + u_t^+ - u_t^- \le E_{\max}, \quad \forall t \tag{11g}$$

where $\boldsymbol{\kappa}_{da}$ is the index set for worst uncertainty points $\widetilde{P}_{t,k}^{W,av}$ which are dynamically generated in (SP1) during the solution procedure. According to [33], the objective function in (SP1) contains the summation of nonnegative slack variables $(\boldsymbol{o}^+, \boldsymbol{o}^-, \boldsymbol{P}^+, \boldsymbol{P}^-, \boldsymbol{q}^+, \boldsymbol{q}^-, \boldsymbol{s}^+, \boldsymbol{s}^-, \boldsymbol{u}^+, \boldsymbol{u}^-)$, which evaluates

Table 2: Parameters of WF-ESS.

η_c	η_d	E_{min} (MWh)	E_{max} (MWh)	E_0 (MWh)	P^W_{max} (MW)
0.95	0.95	10	50	30	75
P^C_{max} (MW)	P^D_{max} (MW)	C_W (DKK/MWh)	C_E (DKK/MWh)	-	-
10	10	196	3.719	-	-

Note: parameters are set according to [15] except for C_W and C_E. In our simulation we set C_W and C_E larger than those in [15], the main purpose of which is to artificially increase the difficulty of WF-ESS to obtain profit in the markets to verify the feasibility of our proposed method.

the violation associated with the solution from (MP1) and can be explained as unfollowed uncertainties due to operational limitations of WF-WSS. Hence, to solve (SP1) is to find the worst point $\widetilde{P}^{W,av}_{t,k}$ in $\boldsymbol{U}_{W,da}$ given the day-ahead offering solution.

With respect to the nth balancing/real-time offering/operating decision-making model proposed in Section 3.3, by using C&CG method for reformulating, its master problem (namely, MP2) and subproblem (namely, SP2) are established in Appendix A.

Moreover, no matter with respect to {(MP1), (SP1)} or {(MP2), (SP2)}, the solution procedure can be summarized as follows [34]:

(1) $\boldsymbol{\kappa} \longleftarrow \phi, k \longleftarrow 1, \Psi \longleftarrow +\infty$, define feasibility tolerance Δ;

(2) **while** $\Psi \geq \Delta$ **do**

(3) Solve (MP), obtain optimal solution of (MP) $\boldsymbol{P}$;

(4) Solve (SP) with $\boldsymbol{P}$, get solution $(\Psi, \widetilde{P}^{W,av}_{t,k})$;

(5) $\boldsymbol{\kappa} \longleftarrow \boldsymbol{\kappa} \cup k, k \longleftarrow k + 1$;

(6) **end while**.

After the convergence of the abovementioned solution procedure, the optimal stochastic-robust day-ahead offering solution can be obtained by solving (MP1) for the last time; similarly, the optimal stochastic-robust balancing/real-time offering/operating solution for time unit n can be obtained by solving (MP2) for the last time. Moreover, it is obvious that if Δ is set to a very small positive value, a very important function of (SP1) and (SP2) is to tell whether the available wind power uncertainties could be well accommodated or not.

4. Simulation and Comparisons

4.1. Case Design. In this subsection, for the purpose of demonstrating our simulation and comparisons more lucidly, we introduce an experimental case design concretely. In our case, an integrated WF-ESS, which contains one wind turbine and one general energy storage device, participates as a "price taker" in both the day-ahead and one-price balancing markets. In the studied WF-ESS, WF and ESS are considered as being connected on the same node (same location) in the power system, Figure 3 simply demonstrates the relationship between the studied WF-ESS and spot EM (main grid).

A delivery day is discretized into 24 time units with 1 hour for the duration of each time unit. The technical and economic parameters for this WF-ESS are listed in Table 2 [15].

All the dynamic uncertainty sets for available wind power outputs, joint stochastic scenarios for day-ahead, and balancing prices (applied in day-ahead stage), as well as joint stochastic scenarios for balancing prices (applied in balancing stages), are constructed and generated based on historical data. Specifically, the historical hourly available wind power data are generated by using the power curve function in [35] and the hourly mean wind speed data in a Chinese city from September 1st to November 30th, 2016 [35]. Due to the inexistence of spot electricity markets in China, it is applied as the historical day-ahead and balancing prices data the ones from DK-West area in the Nord Pool market during the same date range. Because the Nord Pool market is of two-price balancing market, up-/downregulation prices are different and one or the other of them is equal to the day-ahead one at any specific time unit. So we take the different one as the balancing price in the one-price balancing market [15]. Our model series are solved for every delivery day over the last 30 days (30 test days) in that date range. Take one delivery day, for example, in the day-ahead stage, historical available wind power and prices data before this delivery day are used to construct and generate the available wind power dynamic uncertainty set and joint stochastic scenarios for day-ahead and balancing prices corresponding to all time units of this delivery day. Moreover, in the nth balancing stage, available wind power dynamic uncertainty set and joint stochastic scenarios for balancing prices corresponding to the rest time units of this delivery day are dynamically updated from the ones constructed and forecasted in the day-ahead stage based on newly added intra-day historical data which are considered as being realized or accurately forecasted as time went on to the nth balancing stage.

All simulation and comparisons are implemented by utilizing the Matlab R2014a software on a PC laptop with an Intel Core i7 at2.1 GHz and 8 GB memory.

4.2. Calculation Results Analysis. In this subsection, simulation of our proposed progressive stochastic-robust hybrid optimization model series is implemented to obtain the WF-ESS's optimal day-ahead/balancing offering and real-time operating strategies for the 30 test days mentioned in Section 4.1. Primary parameters are set as $\rho = 0.6$, $\gamma = 0.5$, $\alpha = 0.05$, $card(\Theta_{da}) = 100$, $card(\Theta_{re,n}) = 100$, $\Delta = 0.000001$. It should be noted that the numbers of joint stochastic scenarios of prices we used in day-ahead and balancing market stages ($card(\Theta_{da}) = 100$, $card(\Theta_{re,n}) = 100$) are obtained by method of scenario reduction. The specific approach is as

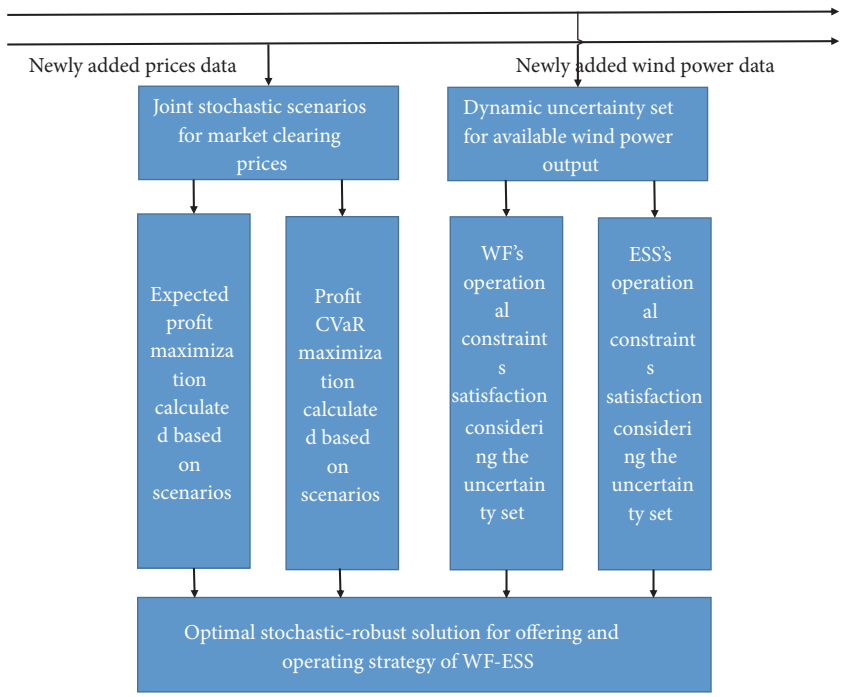

Figure 2: Theoretical flowchart of our proposed stochastic-robust optimization methodology.

follows, Firstly, before each decision-making, method in [15] is applied to generate or update the day-ahead and balancing price probability density function, respectively, based on the updated prices historical data. Secondly, before each decision-making, Monte Carlo sampling method is used to generate 10,000 day-ahead-balancing prices joint stochastic scenarios or balancing prices joint stochastic scenarios based on the corresponding probability density function. Finally, using the method in [36], the similar scenarios are further reduced by comparing the probability distances between the scenarios, and finally 100 scenarios used in the simulation are formed. Since the main innovations in this paper do not involve the generation and reduction of stochastic scenarios, please refer to [15, 36] for specific scenario generation and reduction methods.

Moreover, because simultaneous charging and discharging is prohibited and it has not been defined in our models the binomial variables representing the state of charge, the real-time operating power of ESS in time unit t (namely, $P_{ESS,t}$) is actually the net value between P_t^D and P_t^C:

$$P_{ESS,t} = P_t^D - P_t^C \tag{12}$$

Since (12) is introduced in our model series, the actual charge or discharge power of ESS is $P_{ESS,t}$, not P_t^C and P_t^D (P_t^C and P_t^D are auxiliary variables), which means ESS charges in time unit t when $P_{ESS,t} \leq 0$ and discharges in time unit t when $P_{ESS,t} > 0$.

4.2.1. Available Wind Power Uncertainty Accommodation Test. As mentioned in Section 3.4, after the solution procedure is terminated (no matter with respect to {(MP1), (SP1)} or {(MP2), (SP2)}), a very important function of (SP1) and (SP2) is to tell whether the available wind power uncertainties could be well accommodated or not. That is because, taking the day-ahead stage, for example, if the real-time available wind power uncertainties from time unit 1 to 24 of a delivery day cannot be well accommodated based on reasonable adjustments from the obtained nominal balancing/real-time offering/operating strategies, there should be $\Psi_{SP1} \geq \Delta$; otherwise, there should be $0 \leq \Psi_{SP1} \leq \Delta$.

To confirm the available wind power uncertainty accommodation ability of our proposed progressive stochastic-robust hybrid optimization model series, Figure 4 depicts the final obtained Ψ_{SP1} ("Psi(SP1)" in Figure 2) and Ψ_{SP2} ("Psi(SP2)" in Figure 2) values of the 30 test days, respectively (where "Delta" represents Δ).

From Figure 4, the following can be seen.

(1) In every day of these 30 test days, relationship $0 \leq \Psi_{SP1} \leq \Delta$ is valid, which means solutions obtained in day-ahead decision-making stages using the day-ahead model in our proposed model series have left enough rooms for WF-ESS's power adjustments so as to accommodate the real-time available wind power uncertainties.

(2) In every time unit of these 30 test days, relationship $0 \leq \Psi_{SP2} \leq \Delta$ is valid, which means solutions obtained in balancing decision-making stages using the progressive balancing/real-time models in our proposed model series have left enough rooms for WF-ESS's power adjustments so as to accommodate the real-time available wind power uncertainties in the rest time units of the corresponding delivery day.

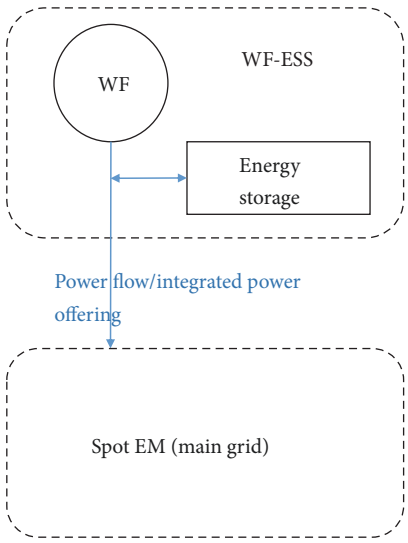

Figure 3: Relationship between the studied WF-ESS and spot EM (main grid).

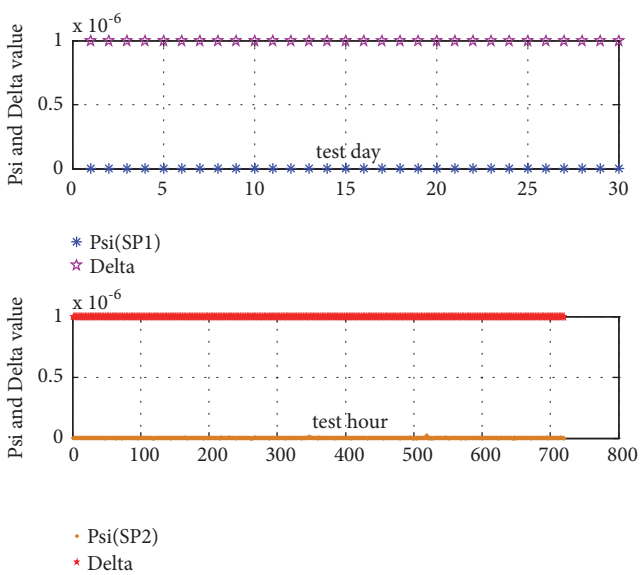

Figure 4: The final obtained Ψ_{SP1}, Ψ_n, and Ψ_{SP2} values of the 30 test days.

Therefore, it is validated that by implementing our proposed progressive stochastic-robust hybrid optimization model series, the internal power compensation potential of WF-ESS can be adequately utilized so as to guarantee the realizations of real-time available wind power uncertainties accommodations.

4.2.2. Day-Ahead and Balancing Offerings Analysis. By implementing our proposed progressive stochastic-robust hybrid optimization model series, WF-ESS's day-ahead and balancing offerings in the 30 test days can be finally obtained and demonstrated in Figure 5.

From Figure 5, the following can be concluded.

In the day-ahead stages, WF-ESS usually offers larger joint power outputs when the day-ahead prices are relatively high and offers smaller joint power outputs when the day-ahead prices are relatively low. In the balancing stages, WF-ESS usually offers positive joint power outputs (provide upregulations) when balancing prices are higher than day-ahead ones, and offers negative joint power outputs (provide downregulations) when balancing prices are lower than day-ahead ones. According to [32], on one hand, the strategy of "selling more at relatively high prices" and "selling less at relatively low prices" in day-ahead market helps in profit improvement. On the other hand, if the balancing price is higher than the day-ahead one corresponding to the same time unit, it shows that there is a problem of "power shortage" in balancing market, and providing upregulation in this balancing stage can make the provider benefit further; conversely, it shows that there is a problem of "load shortage" in balancing market, and providing downregulation in this balancing stage can make the provider benefit further. Therefore, it is validated that by implementing our proposed progressive stochastic-robust hybrid optimization model series, the arbitrage potential of WF-ESS can be reasonably utilized so as to make itself strategically participate in multistage spot EMs for total profit improvement. However, uncertainties from spot EM prices and real-time available wind power outputs may sometimes interfere with WF-ESS's offering and operating decision-makings; that is why the day-ahead offerings at the 14th and 530th time units etc. (corresponding to 13 to 14 p.m. in November 1st and 1 to 2 a.m. in November 22nd, respectively), as well as the balancing offerings at 275th and 369th time units etc. (corresponding to 10 to 11 a.m. in November 11th and 8 to 9 a.m. in November 15th, respectively), deviate from the behavior patterns summarized above.

In order to facilitate the description, offering, and operating strategies obtained by our proposed progressive stochastic-robust hybrid optimization model series are called strategy 1 in the rest of this paper. Hence, WF-ESS's actual daily profits of these 30 test days obtained by strategy 1 are listed in Table 3. Although it is obvious from Table 3 that WF-ESS can earn considerable daily profits during these 30 test day by strategy 1, advantages of our proposed progressive stochastic-robust hybrid optimization model series still need to be further validated by profit comparisons with other existed decision-making methods.

Moreover, by implementing our simulation in this subsection, it takes an average of 11.7 seconds for each of our day-ahead model to calculate and takes an average of 5.2 seconds for each of our balancing/real-time model to calculate. It is generally known that day-ahead market starts at least 12 hours before the delivery day and balancing market begins few minutes to half an hour in advance [32]; that is to say, low computational time makes our proposed model series feasible for obtaining WF-ESS's offering and operating strategies in day-ahead and balancing stages.

4.3. Profit Comparison. In this subsection, WF-ESS's profit earned by strategy 1 is compared with that earned by implementing some other existed methods. Similar to this

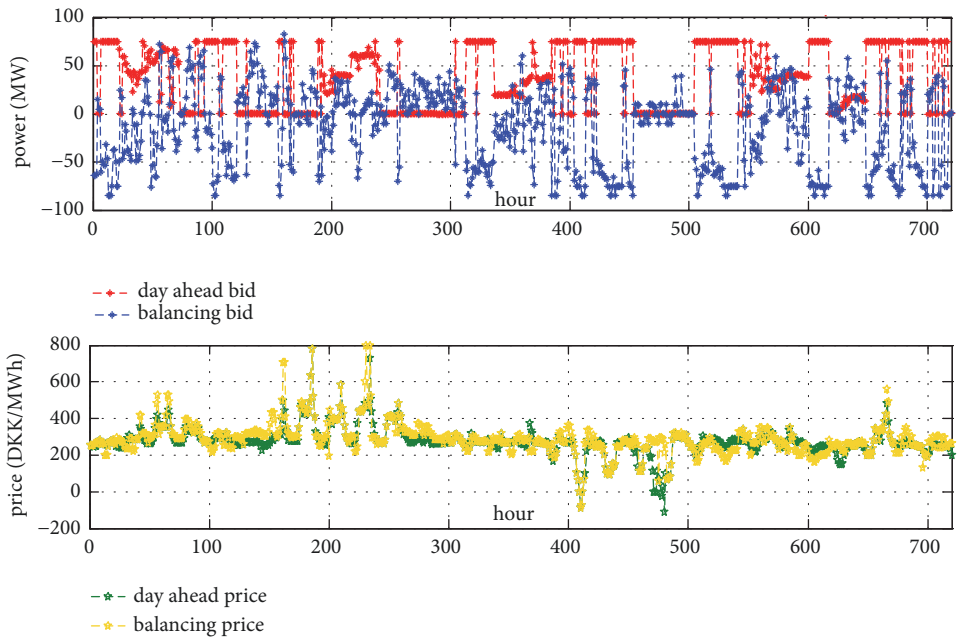

Figure 5: WF-ESS's day-ahead and balancing joint offerings in 30 test days.

Table 3: WF-ESS's actual daily profits of these 30 test days.

test day	Nov.2016									
	1	2	3	4	5	6	7	8	9	10
daily profit (10^4 DKK)	4.53	12.63	19.48	13.03	9.36	5.92	9.80	11.20	25.29	26.73
test day	Nov.2016									
	11	12	13	14	15	16	17	18	19	20
daily profit (10^4 DKK)	13.39	4.04	4.38	4.83	6.21	12.48	4.76	3.41	2.50	1.00
test day	Nov.2016									
	21	22	23	24	25	26	27	28	29	30
daily profit (10^4 DKK)	5.34	7.50	7.90	9.52	12.55	7.00	3.76	11.40	4.82	2.26
total monthly profit(10^4 DKK)	266.75				average daily profit (10^4 DKK)				8.89	

Note: Take one test day for example, after implementing the proposed model series for this day, WF-ESS's optimal offering and operating strategies can be obtained. Hence, WF-ESS's actual daily profit means the daily profit calculated by using the obtained strategies and the realized (actual) available wind power outputs and prices data.

paper, it has been established a model series in [15]. By sequentially solving each model in the model series, the offering and/or operating solutions corresponding to each market stage will be obtained one by one. The introduction of the model series is conducive to the use of dynamically updated electricity prices and wind power data. Hence, it has already been verified the strategy obtained by implementing model series proposed in [15] can make WF-ESS earn more profit than many other methods such as the expected utility maximization (EUM) one and filter control (FC) one which do not involve the use of dynamically updated electricity prices and wind power data. However, different from our paper, in [15], the day-ahead market decision-making model is a stochastic optimization model based on the joint stochastic scenarios of day-ahead, balancing electricity prices, and wind power outputs. Each balancing market decision-making model is only a linear affine function and does not involve reoptimization problems. In this subsection, naming strategy obtained by method in [15] as strategy 2, comparison of our proposed strategy 1 with strategy 2 is mainly conducted.

With respect to strategy 2 bringing here for comparison, both the forecasted scenarios for clearing prices and real-time available wind power outputs which are applied to optimization are based on the same historical data mentioned in Section 4.1. Moreover, for methods for scenario generation and reduction refer to [15, 36].

Figure 6 demonstrates WE-ESS's daily actual profits of these 30 test days obtained by strategy 1 and by strategy 2 respectively.

From Figure 6, it is obvious that in most test days, WF-ESS's actual daily profits obtained by strategy 1 are more than those obtained by strategy 2, which validates that WF-ESS can earn more profit by implementing our proposed progressive stochastic-robust hybrid optimization model series than

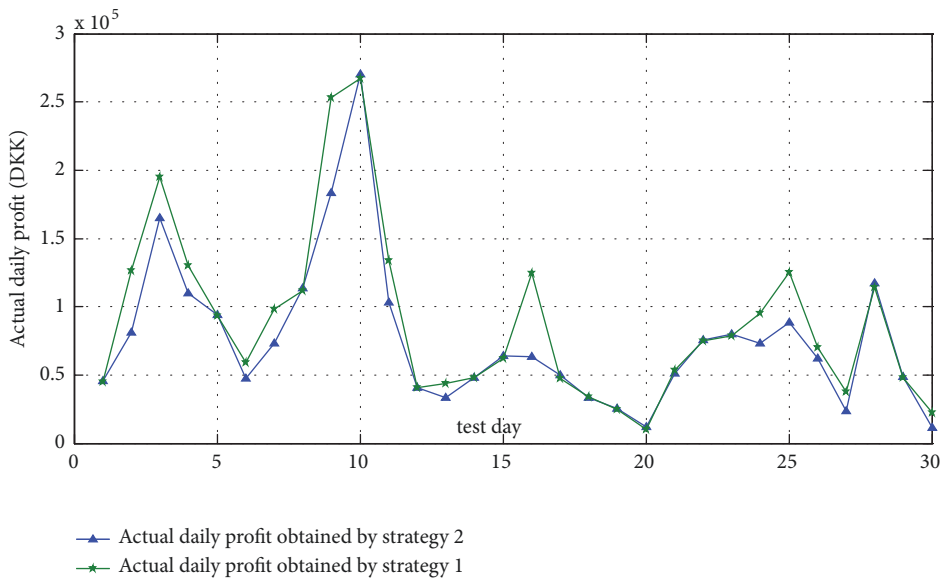

Figure 6: Comparison of WF-ESS's actual daily profits obtained by strategyies1 and 2.

method proposed in [15]. The most important reasons are as follows.

(1) The real-time operating linear decision rule proposed in [15], to a certain extent, limits the feasible range of real-time power adjustments because the affine matrix **D** proposed in [15] for constructing the real-time linear decision rule, which is responsible for generating WF-ESS's real-time power adjustments, is only optimized in day-ahead stage and is not dynamically adjusted by using newly added data in the progressive balancing stages. However, real-time power adjustments obtained by our proposed methods are dynamically optimized in progressive balancing stages based on newly updated data, which does not limit the feasible range of real-time power adjustments so as to make our strategy less conservative in pursuing more profit.

(2) Strategy 2 only optimizes powers of ESS in day-ahead decision-making models while in real-time operating linear decision rules, powers of ESS are not reoptimized so as to make WF-ESS participate in balancing markets strategically for pursuing more total profits. However, strategy 1 optimizes powers of ESS not only in day-ahead decision-making models but also in balancing/real-time models, which means powers of ESS are dynamically reoptimized in balancing stages so as to make WF-ESS participate in balancing markets strategically for pursuing more total profits.

Moreover, it takes an average of 138.9 seconds by implementing strategy 2 for each day-ahead market stage and takes an average of 0.1 seconds by implementing strategy 2 for each balancing market stage. Due to the only SO based structure, the number of variables and constraints in day-ahead model in [15] is much more than that in our day-ahead model. This makes the computational time of day-ahead model in [15] much higher than that of ours. Due to the linear structure, the computational complexity of balancing/real-time model in [15] is lower than that of ours. This makes our balancing/real-time model to be more time-consuming.

In summary, by implementing strategies 1 and 2 on these 30 test days, the profit improvement of our proposed model series compared with other works can be numerically concluded (with totally 37.28×10^4 DKK in profit improvement compared with strategy 2). In addition, although implementing our balancing/real-time model is more time-consuming, it is still feasible for taking our model series in practice because balancing market begins few minutes to half an hour in advance [34].

4.4. Sensitivity Analysis. Parameters of our proposed model series will significantly influence the result of the formulations. In this subsection, two important parameters are taken into account, which are parameter ρ of the dynamic uncertainty set and weighting parameter γ controlling the trade-off between the expectation and CVaR. Figure 7 depicts a relation curve between the obtained average and CVaR values of WF-ESS's daily profit of these 30 test days, which corresponds to different ρ values. More concrete details about the influence of ρ on the result of the formulations are listed in Table 4. Moreover, a Pareto efficient frontier between the obtained average and CVaR values of WF-ESS's daily profit of these 30 test days is demonstrated in Figure 8, which corresponds to different γ values. More concrete details about the influence of γ on the result of the formulations are listed in Table 5.

From Figure 7 and Table 4, the following can be concluded.

(1) When ρ is less than an appropriate value (namely, $\rho \leq 0.6$), WF-ESS's average daily profit increases with the

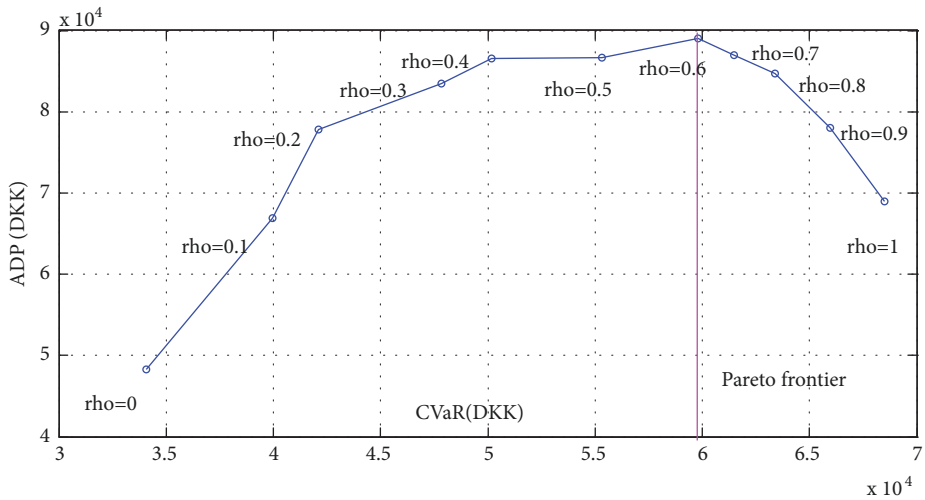

Figure 7: Relation curve between the average and CVaR values of WF-ESS's daily profit as ρ increases.

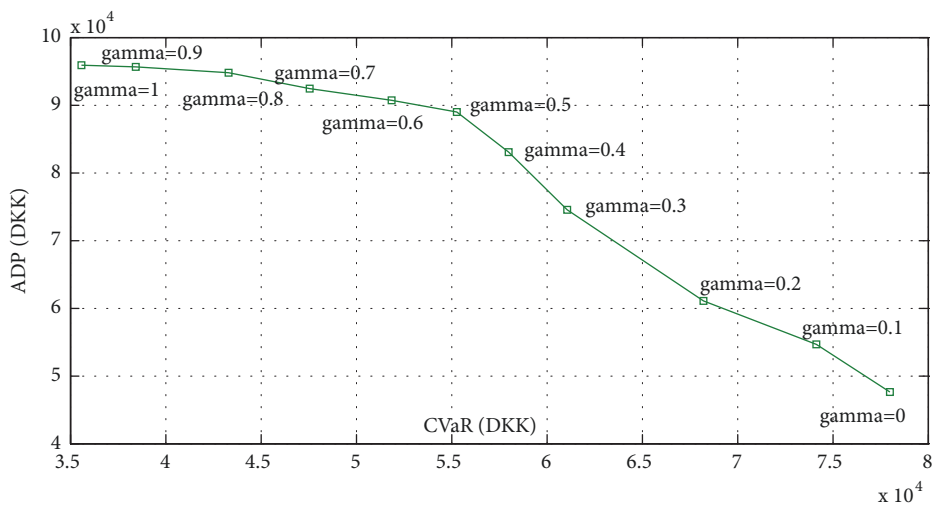

Figure 8: Pareto efficient frontier between the average and CVaR values of WF-ESS's daily profit as γ increases.

Table 4: Average and CVaR values of WF-ESS's daily profit as ρ increases.

ρ	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
ADP (10^4DKK)	4.83	6.69	7.78	8.35	8.65	8.67	8.89	8.68	8.47	7.80	6.90
CVaR (10^4DKK)	3.41	3.99	4.21	4.78	5.02	5.53	5.98	6.14	6.34	6.59	6.84

Note: ADP is the abbreviation of the "WF-ESS's average daily profit". WF-ESS's average daily profit mentioned here means the average value calculated by using WF-ESS's actual daily profits of 30 test days. CVaR in Tables 4 and 5 is calculated based on the actual profits of 30 test days and the frequency of each profit (1/30). The specific approach is: Firstly, the actual profits of the 30 test days are arranged from small to large, and the cumulative frequency of less than each actual profit is calculated; Secondly, it is approximately considered as VaR_α the actual profit with the cumulative frequency closest to the α value; Finally, the conditional average value of all actual profits less than VaR_α is calculated, and considered as CVaR_α.

Table 5: Average and CVaR values of WF-ESS's daily profit as γ increases.

γ	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
ADP (10^4DKK)	4.76	5.46	6.11	7.45	8.31	8.89	9.07	9.24	9.48	9.56	9.59
CVaR (10^4DKK)	7.79	7.41	6.82	6.11	5.80	5.53	5.18	4.76	4.33	3.84	3.56

increase of ρ. When ρ is greater than that value, WF-ESS's average daily profit decreases with the increase of ρ. The main reason for this phenomenon is that, in our model series, a too small ρ value corresponds to a series of too narrow available wind power dynamic uncertainty sets, which make our day-ahead and balancing/real-time decision-making approaches too deterministic to cope with potential risks caused by real-time available wind power uncertainties. Hence, increasing ρ from a too small value helps reduce chances of profit losses due to wind power uncertainty. Conversely, a too large ρ value corresponds to a series of too wide available wind power dynamic uncertainty sets, which make our day-ahead and balancing/real-time decision-making approaches too conservative to pursue more profit. Hence, increasing ρ from a too large value would result in profit losses.

(2) Although WF-ESS's average daily profit fluctuates with the increase of ρ, the CVaR of WF-ESS's daily profit has the monotonic relationship with ρ. Specifically, the CVaR increase with the increase of ρ. That is mainly because, in our model series, the larger the value of ρ is, the more risk-averse the result of the formulations is for the available wind power uncertainties, by which the influence of available wind power uncertainties on WF-ESS's actual daily profit would be weakened effectively.

In conclusion, the right side of the curve depicted in Figure 7 is a Pareto efficient frontier, which means the best choices for ρ values, and there does not exist any solutions making both expectation (average) and CVaR better off at the same time.

From Figure 8 and Table 5, it can be concluded that increasing the weighting parameter γ can better guarantee the average daily profit but sacrifices the CVaR, otherwise the opposite. That is mainly because, in our model series, a larger γ implies a more risk-neutral strategy to the prices uncertainties, by which the influence of prices uncertainties on WF-ESS's actual daily profit would be strengthen effectively. The value selection of γ depends on the attitude of the WF-ESS to prices uncertainties risks and each value of γ maps to one point of the Pareto efficient frontier in Figure 8, which means there does not exist any solution which can make both expectation (average) and CVaR better off at the same time.

5. Conclusion

This paper proposed a progressive stochastic-robust hybrid optimization model series for WF-ESS, as a "price taker" participating in both the day-ahead and balancing markets, to optimally cogenerate offering and operating strategies from the integrated and progressive point of views. Simulation and comparisons based on realistic data have presented some interesting conclusions.

(1) It is validated that by implementing our proposed progressive stochastic-robust hybrid optimization model series, the internal power compensation potential of WF-ESS can be adequately utilized so as to guarantee the realizations of real-time available wind power uncertainties accommodations.

(2) It is validated that by implementing our proposed progressive stochastic-robust hybrid optimization model series, the arbitrage potential of WF-ESS can be reasonably utilized so as to make itself strategically participate in multistage spot EMs for total profit improvement.

(3) Low computational time makes our proposed model series feasible for obtaining WF-ESS's offering and operating strategies in day-ahead and balancing stages.

(4) By implementing the comparison test, significant profit improvement effect of our proposed model series compared with other existing works was numerically concluded. In addition, although implementing our balancing/real-time model is more time-consuming, it is still feasible for taking our model series in practice because balancing market begins few minutes to half an hour in advance.

(5) Sensitivity analyses have reached two Pareto efficient frontiers between the obtained average and CVaR of WF-ESS's daily profit which provides important references for selecting different risk attitudes towards wind power and prices uncertainties, respectively.

Our future work will release the "price taker" assumption and focus on the "price maker" strategies of WF-ESS. Moreover, extending the WF-ESS to other hybrid energy systems such as micro-grid, virtual power plant, and integrated energy system will also be the topic that we will focus on in the future.

Appendix

A. Model Reformulation for the Balancing Stage

With respect to the nth balancing/real-time offering/operating decision-making model proposed in Section 3.3, by using CCG method for reformulating, its master problem (namely, MP2) and subproblem (namely, SP2) are established as follows:

(MP2) Eq. (9a)
s.t. Eqs. (9b)-(9k)

$$0 \le P_t^W + \Delta P_{n,t,k}^W \le \widetilde{P}_{t,k}^{W,av}, \quad t = n+1, n+2, \ldots, T, \ \forall k \in \boldsymbol{\kappa}_{re,n} \tag{A.1a}$$

$$0 \le P_t^C + \Delta P_{n,t,k}^C \le P_{\max}^C, \quad t = n+1, n+2, \ldots, T, \ \forall k \in \boldsymbol{\kappa}_{re,n} \tag{A.1b}$$

$$0 \le P_t^D + \Delta P_{n,t,k}^D \le P_{\max}^D, \quad t = n+1, n+2, \ldots, T, \ \forall k \in \boldsymbol{\kappa}_{re,n} \tag{A.1c}$$

$$E_{n,t,k} = E_n + \sum_{j=n+1}^{t} \left(P_j^C + \Delta P_{n,j,k}^C\right) \eta_C \Delta t - \sum_{j=n+1}^{t} \left[\frac{\left(P_j^D + \Delta P_{n,j,k}^D\right)}{\eta_D} \right] \Delta t, \quad t = n+1, n+2, \ldots, T, \ \forall k \in \boldsymbol{\kappa}_{re,n} \tag{A.1d}$$

$$0 \le E_{n,t,k} \le E_{\max}, \quad t = n+1, n+2, \ldots, T, \ \forall k \in \boldsymbol{\kappa}_{re,n} \tag{A.1e}$$

(SP2) Ψ_{SP2}

$$= \max_{\widetilde{\boldsymbol{P}}_{w,av} \in \boldsymbol{U}_{W,n}} \min_{\boldsymbol{o}^+, \boldsymbol{o}^-, \boldsymbol{P}^+, \boldsymbol{P}^-, \boldsymbol{q}^+, \boldsymbol{q}^-, \boldsymbol{s}^+, \boldsymbol{s}^-, \boldsymbol{u}^+, \boldsymbol{u}^-, \Delta \boldsymbol{P}_{ba,n}} \sum_{t=n+1}^{T} \left(o_t^+ + o_t^- + p_t^+ + p_t^- + q_t^+ + q_t^- + s_t^+ + s_t^- + u_t^+ + u_t^-\right) \tag{A.2a}$$

$$\begin{aligned} &\text{s.t. } o_t^+ \ge 0, \\ &o_t^- \ge 0, \\ &p_t^+ \ge 0, \\ &p_t^- \ge 0, \\ &q_t^+ \ge 0, \\ &q_t^- \ge 0, \\ &s_t^+ \ge 0, \\ &s_t^- \ge 0, \\ &u_t^+ \ge 0, \\ &u_t^- \ge 0, \\ &t = n+1, n+2, \ldots, T \end{aligned} \tag{A.2b}$$

$$P_t^r = \boldsymbol{D}^T \left(\boldsymbol{P}_t + \Delta \boldsymbol{P}_{n,t}\right) - P_t^{da}, \quad t = n+1, n+2, \ldots, T \tag{A.2c}$$

$$0 \le P_t^W + \Delta P_{n,t}^W + o_t^+ - o_t^- \le \widetilde{P}_t^{W,av}, \quad t = n+1, n+2, \ldots, T \tag{A.2d}$$

$$-r \le P_t^W + \Delta P_{n,t}^W - P_{t-1}^W - \Delta P_{n,t-1}^W + p_t^+ - p_t^- \le r, \quad t = n+2, n+3, \ldots, T \tag{A.2e}$$

$$0 \le P_t^C + \Delta P_{n,t}^C + q_t^+ - q_t^- \le P_{\max}^C, \quad t = n+1, n+2, \ldots, T \tag{A.2f}$$

$$0 \le P_t^D + \Delta P_{n,t}^D + s_t^+ - s_t^- \le P_{\max}^D, \quad t = n+1, n+2, \ldots, T \tag{A.2g}$$

Eqs. (9q)

$$0 \le E_{n,t} + u_t^+ - u_t^- \le E_{\max}, \quad t = n+1, n+2, \ldots, T \tag{A.2h}$$

where $\boldsymbol{\kappa}_{re,n}$ is the index set for worst uncertainty points $\widetilde{P}_{t,k}^{W,av}$ which are dynamically generated in (SP2) during the solution procedure. According to [28], the objective function in (SP2) contains the summation of nonnegative slack variables $(\boldsymbol{o}^+, \boldsymbol{o}^-, \boldsymbol{P}^+, \boldsymbol{P}^-, \boldsymbol{q}^+, \boldsymbol{q}^-, \boldsymbol{s}^+, \boldsymbol{s}^-, \boldsymbol{u}^+, \boldsymbol{u}^-)$, which evaluates the violation associated with the solution from (MP2) and can be explained as unfollowed uncertainties due to operational limitations of WF-WSS. Hence, to solve (SP2) is to find the worst point $\widetilde{P}_{t,k}^{W,av}$in $\boldsymbol{U}_{W,n}$ given the real-time operating solution for time unit n.

Nomenclature

t, n:	Indices for time unit
T:	Number of time unit for a delivery day
$\widetilde{P}_t^{W,av}, \widetilde{\lambda}_t^{da}, \widetilde{\lambda}_t^{re}$:	Random variables of real-time available wind power output, day-ahead, and balancing prices for time unit t
$\{\widetilde{P}_t^{W,av}\}_{t=1}^T, \{\widetilde{\lambda}_t^{da}\}_{t=1}^T, \{\widetilde{\lambda}_t^{re}\}_{t=1}^T$:	Uncertainties for real-time available wind power outputs, day-ahead, and balancing prices estimated in the day-ahead stage
$\{\widetilde{P}_t^{W,av}\}_{t=n+1}^T, \{\widetilde{\lambda}_t^{re}\}_{t=n}^T$:	Uncertainties for real-time available wind power outputs and balancing prices estimated (latest updated) in the nth balancing stage
$P_t^{W,av}, \lambda_t^{da}, \lambda_t^{re}$:	Realized real-time available wind power output, day-ahead, and balancing prices for time unit t
P_t^{da}:	WF-ESS's day-ahead offering volume for time unit t
P_t^r:	WF-ESS's real-time decisions for buying/selling up-/downregulations in balancing market for time unit t
$\widehat{P}_t^W, \widehat{P}_t^C, \widehat{P}_t^D$:	Nominal operating solutions for WF's dispatched power output, ESS's dispatched power charge, and discharge for time unit t
P_t^W, P_t^C, P_t^D:	Adjusted operating solutions for WF's dispatched power output, ESS's dispatched power charge, and discharge for time unit t
SoC_{n-1}:	ESS's state of charge for time unit t

$\widehat{E}_t$: ESS's nominal residual energy at the end of time unit t

E_t: ESS's nominal residual energy at the end of time unit t.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

Authors' Contributions

Yuwei Wang established the model, implemented the simulation, and wrote this article; Huiru Zhao and Peng Li guided the research.

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