Risk-Constrained Optimal Bidding Strategy for Pairing of Wind and Demand Response Resources

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***Abstract*—Wind power represents a significant percentage of the Spanish generation mix and this trend will increase due to the commitment of the European Union to the full deployment of Directive 2009/28/EC. The increasing penetration of intermittent renewable energy, and the development of advanced information and communication technologies, give rise to questions on how additional flexibility obtained from loads can be used in order to optimize the use of resources and assets. This paper proposes a comprehensive stochastic decision making model for the coordinated operation of wind power producers and demand response (DR) aggregators participating in the day-ahead market. In order to account for the uncertainty around the true outcomes of day-ahead prices and wind power, a minimum conditional value at risk term has been included in the model formulation. Numerical results illustrate how the proposed bidding strategy for wind and demand response (DR) pairing increases the expected benefit of both resources and reduces the related risk.**

***Index Terms*—Bidding strategy, conditional value at risk (CVaR), demand response (DR), electricity market, risk aversion, wind power.**

NOTATION

Indices and Sets

$t, t1$	Time period (h).
Ω^t	Set of time periods [0, ..., 24].
w	Wind scenario.
Ω^w	Set of wind scenarios.
s	Day-ahead price scenario.
Ω^s	Set of day-ahead price scenarios.

Parameters

W	Installed wind capacity (MW).
α	Per unit confidence level.
β	Weighting parameter for cost versus risk tradeoff.
ξ_w	Wind production scenario probability.
ξ_s	Day-ahead price scenario probability.
$\lambda_{t,s}$	Day-ahead price at hour t and price scenario s (€/MWh).
$\overline{\lambda}_{t,s}$	Average day-ahead price at hour t and price scenario s (€/MWh).
$\lambda^+_{t,s}$	Expected intraday price for positive deviations at hour t and price scenario s (€/MWh).
$\lambda^-_{t,s}$	Expected intraday price for negative deviations at hour t and price scenario s (€/MWh).
$\varepsilon_{t,t1}$	Own ($\varepsilon_{t,t}$) and cross price ($\varepsilon_{t,t1}$) elasticity of demand.
d_t	Aggregated demand (MW).
$wf_{t,w}$	Wind production forecast for scenario w and hour t (MW).
DR^{0+}_t	Upper positive demand response (DR) level at hour t (MW).
DR^{0-}_t	Lower negative DR level at hour t (MW).
$\Delta\mathrm{DR}^+_t$	Distance between two consecutive values of DR^+_t at hour t (MW).
$\Delta\mathrm{DR}^-_t$	Distance between two consecutive values of DR^-_t at hour t (MW).
k	Blocks used in the linearization process.
$\mathrm{DR}^{\max +}_t$	Higher positive DR level at hour t (MW).
$\mathrm{DR}^{\max -}_t$	Higher negative DR level at hour t (MW).
y^+_t	Positive activated DR price at hour t (€/MWh).
y^-_t	Negative activated DR price at hour t (€/MWh).

Variables

$\mathrm{EP}_{s,w}$	Expected profit of the wind power producer (WPP) at scenarios s and w (€).
$\eta_{s,w}$	Auxiliary variable used for conditional value at risk (CVaR) calculation at scenarios s and w.
w_t	Wind offer in the day-ahead market at hour t (MW).
$\rho^+_{t,w}$	Expected hourly positive corrected deviation at hour t and wind scenario w (MW).
$\rho^-_{t,w}$	Expected hourly negative corrected deviation at hour t and wind scenario w (MW).
$\mathrm{dr}^+_{t,w}$	Expected positive activated DR at hour t and wind scenario w (MW).
$\mathrm{dr}^-_{t,w}$	Expected negative activated DR at hour t and wind scenario w (MW).
$\zeta^+_{t,s}$	Positive day-ahead price deviation at hour t and price scenario s (€).
$\zeta^-_{t,s}$	Negative day-ahead price deviation at hour t and price scenario s (€).

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$\mathrm{DR}_{t,s}$ DR at hour t and price scenario s (MW).
DR_t^+ Contracted positive DR at hour t (MW).
DR_t^- Contracted negative DR at hour t (MW).
$\sigma_{t,w}^+$ Expected hourly positive deviation at hour t and wind scenario w (MW).
$\sigma_{t,w}^-$ Expected hourly negative deviation at hour t and wind scenario w (MW).
$n_{t,w}$ Binary variable controlling wind forecast deviation at hour t and wind scenario w: 1 if positive, 0 otherwise.
$\upsilon_{t,s}$ Binary variable controlling price forecasting deviation at hour t and price scenario t: 1 if positive, 0 otherwise.
$\kappa_{k,t}$ Auxiliary binary variable used for the formulation of the required linearization at block b and hour t: 1 if positive, 0 otherwise.
$\partial_{k,t}$ Auxiliary binary variable used for the formulation of the required linearization at block b and hour t: 1 if positive, 0 otherwise.
$\mathrm{bin}_{t,w}$ Auxiliary binary variable used for the formulation of the required linearization at hour t and wind scenario w: 1 if positive, 0 otherwise.
$\mathrm{var}_{t,w}$ Auxiliary continuous variable used for the formulation of the required linearization at hour t and wind scenario.
c DR price (€/MWh).

I. Introduction

Renewable generation technologies have been promoted by policy makers throughout the years in an effort to increase the sustainability of electric power systems. The intermittent nature of wind and photovoltaic resources make them difficult to predict. Over the past years wind power has been one of the fastest developing clean technologies, reaching a considerable penetration in electric power systems. Because of the intermittent nature of this type of generation and possible unforeseen variations in power over a short period of time, most of the markets in place impose a penalty on the deviation between the day-ahead bid and the real output. Therefore, the bidding strategy is a critical issue for renewable power producers. In this paper, the problem of optimizing energy bids for an independent WPP taking part in a competitive electricity market is analyzed. It is assumed that the WPP is subject to financial penalties for generation shortfall. Over-generation is compensated at a lower price than in the day-ahead market.

Providing an appropriate context for the participation of WPPs in a competitive electricity market to achieve profit through a market mechanism seems the best way to encourage and support their integration. According to [1], support schemes should be designed to give more market signals to WPPs. Hiroux and Saguan [1] argue that adequate market signals to WPPs can be beneficial to improve the selection of wind sites (considering temporal patterns, congestions, and losses), to improve maintenance planning, the combination with other technologies, to incorporate portfolio effects and to add transparency concerning the total cost of promotion policy.

This paper focuses on the improvement in bidding strategies for a WPP through the combination with other technologies, particularly DR. A crucial role in a high-penetration renewable electricity future is foreseen for demand-side options, taking advantage of its flexibility to allocate wind deviations. Power systems will need to deploy advanced metering, real-time tariffs, and behind-the-meter load management to make DR options a reality. DR can be defined as the incentive payment received by consumers (or demand aggregators) to reduce their electricity consumption in times of high-energy prices, increasing the electricity consumption at times of low prices. This paper enhances this approach, triggering demand responsiveness not only by market prices, but also by WPP requirements, since decreasing the amount of negative imbalances is deemed crucial for an optimal bidding strategy.

The uncertainty associated with nondispatchable technologies introduces risk into renewable power producers bidding strategies. Variability and uncertainty are not unique to stochastic generation resources. Similar challenges are posed by aggregated electricity demand and electricity prices in the day-ahead market. Therefore, risk measuring plays a fundamental role in optimization under uncertainty, providing valuable information to decision makers. The proposed model incorporates risk aversion by constraining the volatility of the expected cost through CVaR assessment, avoiding over-conservative solutions.

A. Literature Review

Several methods have been proposed to cope with the variability and intermittency of wind power, decreasing its imbalance costs. Moghaddam *et al.* [2] proposed a risk-averse profit-based optimal operation strategy of a combined wind farm-cascade hydro system in an electricity market, using hydro plants to compensate wind power forecast errors. A coordinated operation of a wind farm and a pumped hydro storage plant based on a day-ahead power output forecast is proposed in [3], including a chance-constrained and scenario-based stochastic formulation. Different strategies of a combined wind-hydro unit in the Iberian market have been proposed in [4], exploiting synergies between both technologies. The impact of risk management and optimal bidding for a WPP has been analyzed in [5].

Despite the fact that regulation does not yet allow the aggregation of units belonging to different technologies in a so-called virtual power plant (VPP), different papers have shown the appropriateness of pairing technologies, as described in the literature review. An optimal integrated participation model for wind and photovoltaic energy including DR and storage devices in microgrids has been proposed in [6]. A combined scheduling and bidding algorithm for constructing the day-ahead bidding curve of an electric utility including DR has been presented in [7]. The proposed bidding strategy algorithm dispatches units by optimizing the retailer's DR programs.

A decision framework for optimal pairing of wind and DR resources has been described in [8]. The optimal amount of a paired resource (DR, hydro unit, etc.) to be scheduled in the intraday market to mitigate wind power generation variability using updated wind forecasts at each market stage to schedule the pairing resource as the time horizon approaches real-time dispatch is determined. The considered framework uses a paired resource, such as DR or storage to mitigate the generation scheduling errors inherent to stochastic technologies. Results of this approach indicate that the proposed pairing will significantly reduce the need for an independent system operator to procure additional balancing resources when wind power participates in the day-ahead market. A detailed analysis on the impact of European balancing rules on wind power economics and short-term bidding strategies have been performed in [9]. Different balancing rules applied across Europe are analyzed, evaluating their effects on WPP bidding strategies.

Heydarian-Forushani *et al.* [10] presented a risk-constrained offering strategy of WPPs considering intraday demand response exchange (IDRX). In this context, an IDRX market for trading DR between consumers and WPPs is foreseen. Annual wind and price distributions for the offering strategy in the day-ahead market are considered in the model. Mahmoudi *et al.* [11] presented a joint DR contract through bi-level programming, where the upper level represents WPP decisions and the lower level models the DR aggregator.

B. Contributions

The proposed approach foresees a wind offering strategy in the day-ahead market in which a WPP employs DR to cope with power production uncertainty. To this end, a WPP sets DR contracts with a DR aggregator, where a certain amount of power can be shifted considering the optimality of the WPP bid. The contract is established in two terms: the first one is based on the contracted power, where the price settlement is an endogenous variable of the problem. The second one represents a fixed fee per MW of the activated DR. Costs associated to DR shifting to higher price hours and benefits linked to DR shifting to lower price hours are guaranteed in the problem formulation by the contracted power, regardless of their final utilization. The DR aggregator can, however, further participate in the day-ahead market with the noncontracted DR, increasing the value of its flexibility even more.

The DR aggregator is considered to participate in a price-based DR program, facing the hourly marginal price resulting from the day-ahead energy market. For the bilateral agreement between the WPP and DR aggregator, no time-dependent DR price has been considered in this paper, revealing the inherent value of demand's responsiveness. The WPP enters in a derivative agreement with the DR aggregator, where the DR contracting price is derived from the expected profits and costs of DR shifting or reduction. Its value is determined by the fluctuations in the underlying asset. The application of no time-dependent DR prices for the bilateral agreement between VPP and DR aggregator reduces the uncertainty faced by both counterparties.

According to the presented state of the art, the following contributions can be listed.

1) A novel model is proposed in this paper to include DR in the offering strategy of a WPP. By means of a bilateral agreement between the WPP and the DR aggregator, the WPP is able to participate in a day-ahead market while arranging DR contracts with the DR aggregator to lessen its risk. DR price is an endogenous variable of the problem. Note that the wind offering strategy proposed in [8] is not affected by the DR pairing. Anderson and Cardell [8] defined the optimal amount of DR to schedule in the intraday market. Also, the wind and DR joint strategy is not foreseen in [9], where a summary of the different balancing rules across Europe is presented. The model proposed in [10] trades DR in the intraday market covering the deviations, while the proposed methodology combines wind and DR in the day-ahead market, increasing the benefit of both counterparties. Mahmoudi *et al.* [11] assumed an arbitrary behavior of the DR aggregator, being a buyer from 2 to 5 A.M. and a seller from 9 A.M. to 12 P.M. and from 5 to 9 P.M., while this paper foresees a full integration of WPP and DR.
2) Guarantee that the collaboration with WPP should be beneficial for the DR aggregator. The proposed methodology guarantees cost and benefit recovery for the DR aggregator, while reducing the risk faced by WPP, increasing its expected benefit, this being the major contribution of this paper. None of the methodologies proposed in [8], [10], or [11] ensure that the collaboration with the WPP should be beneficial for the DR aggregator. Due to the arbitrary behavior of the DR aggregator in [11], a beneficial collaboration for the DR aggregator cannot be guaranteed. The proposed methodology guarantees for the DR aggregator higher incomes than those potentially obtained in the market.
3) Definition of the optimal price for the bilateral agreement between WPP and the DR aggregator. Heydarian-Forushani *et al.* [10] and Mahmoudi *et al.* [11] foreseed exogenous DR prices, disregarding the impact of real time prices on the willingness of consumers to modify their behaviors. Heydarian-Forushani *et al.* [10] relied on the existence of an exogenous DR market (IDRX), while the proposed methodology obtains the DR price as the price guaranteeing the DR aggregator to obtain at least the benefit it would obtain in the day-ahead market. The presented methodology includes DR price as an endogenous variable of the problem, therefore, being able to ensure an optimal tradeoff between WPP and DR, benefiting both counterparties. Integrating price responsiveness to the model formulation allows the proposed methodology to consider DR availability to be dependent on real time prices along the considered time horizon.

For the aforementioned reasons, the results of the proposed methodology cannot be compared with the ones of previous works presented in [8], [10], or [11]. Notwithstanding, a comparison with the expected bidding strategy when no DR is contracted is included, outlining the benefits of the proposed strategy.

This paper is organized as follows. The proposed risk-constrained optimal bidding strategy for wind and DR pairing is explained in Section II. Section III presents results for the Iberian day-ahead market. The conclusion is given in Section IV.

II. Problem Formulation

A. Framework

Different assumptions are made in the proposed strategy. First, it is assumed that WPPs submit their energy offers in the day-ahead market while clearing imbalances in the balancing market. Furthermore, WPPs are treated similarly to conventional power plants, being responsible for their bidding strategies and power production variation and subject to financial penalties for generation shortfall. A further assumption is the modeling of DR through its own- and cross-price elasticities. Own-price elasticity accounts for an immediate response to price signals, while cross-price elasticity (also known as elasticity of substitution) refers to the consumer's reaction to the prices in other hours and accounts for load shifting. Estimations on demand own- and cross-price elasticities vary significantly across literature. Spees and Lave [12] presented a comprehensive overview of elasticity computation, summarizing many other studies. The model measures how electricity usage can be shifted from one part of the day to another or reduced in a particular hour in order to use the value of its flexibility. Modeling technical DR programs through which the DR aggregator obtains DR from customers is not the focus of this paper. Through the contract settlement between the WPP and the DR, costs and benefits associated to the equivalent load shifting in the market process are guaranteed. Finally, note that DR accounts for both shifts: shifts that would normally occur during peak hours to off-peak hours in response to a change in the ratio of peak to off-peak prices and shifts from off-peak to peak hours.

The proposed wind offering strategy considers that the DR aggregator can trade DR with the WPP or participate in the day-ahead market. The model determines the optimal offering quantity instead of presenting bidding curves, as shown in other studies. The share of DR contracted for each time slot is such that it guarantees the recovery of the incurred costs and the expected benefits for the DR aggregator as a consequence of load shifting. The price of the foreseen contract is considered as an endogenous variable of the problem. An additional payment is considered every time the contracted DR is activated. Doing so, not only the risk associated to the DR offering strategy in the day-ahead market lowers, but also additional benefits of its flexibility can be foreseen when increasing its consumption during peak hours to accommodate wind power imbalances. Consequently, given the volume of DR contracted by the WPP, the WPP makes its offer in the day-ahead market. Besides day-ahead, balancing market price and wind power forecasts, the risk aversion of the WPP has to be taken into account. The risk aversion of the producer is considered in the model by means of CVaR.

It is worth stressing that decisions resulting from the aforementioned problem are adopted considering the uncertainties associated to the model. The uncertainties considered are related to the following parameters: day-ahead market prices, intraday prices, imbalance prices, and wind power production. Monte Carlo simulation has been used to generate the different required scenarios. Considering a sufficiently large number of elements of the time series, it is possible to represent uncertainty around the true outcomes of wind power production, day-ahead, and imbalance prices.

Additionally, this paper includes the CVaR formulation to quantify the risk assumed during the bidding process procedure against uncertainties [13]. CVaR assessment is able to quantify the risk potential beyond the value at risk (VaR) and represents an appropriate approach to integrate the inherent risk management problem in the bidding strategy, including power production, day-ahead and intraday price uncertainties. According to [14], the discontinuous distribution of VaR may lead to failures in optimization problems. Additionally, the VaR risk measure is nonsensitive to extreme risks, providing a risk limit. On the contrary, CVaR points out the tail mean and provide an estimate of the weighted costs. For a given $\alpha \in (0, 1)$, CVaR is defined as the expected value of the profit smaller than the $(1-\alpha)$ quantile of the profit distribution. In case all scenarios are equiprobable, CVaR is computed as the expected profit in the $(1-\alpha) \times 100\%$ worst scenarios. The CVaR is also known as mean excess loss or average value-at-risk. Based on this claim, CVaR is an adequate risk aversion measure for stochastic optimization problems. García-González *et al.* [15] presented an optimization model to help a hydro-generation company to schedule its hydroelectric units in the very short-term under a competitive environment.

B. Problem Formulation

The objective of the WPP is to maximize the expected profit considering risk constraints and DR costs and benefits recovery. According to the proposed market model, the objective function can be expressed as shown in (1), where CVaR has already been integrated. The decision variables of the problem are w_t, DR_t^+, DR_t^-, $\mathrm{dr}_{t,w}^+$, and $\mathrm{dr}_{t,w}^-$

$$\max_{w_t,\mathrm{DR}_t^+,\mathrm{DR}_t^-,\mathrm{dr}_{t,w}^+,\mathrm{dr}_{t,w}^-}\left(\sum_{w,s}\left((1-\beta)*\xi_w*\xi_s*\mathrm{EP}_{s,w}\right) + \beta*\mathrm{CVaR}\right). \quad (1)$$

The expected profit of the WPP is formulated in (2) and includes the expected incomes of selling energy in day-ahead market. Positive deviations are included in the formulation as additional benefits at the intraday price. The negative deviation penalizes the expected revenue of the WPP. In the same way, contracted DR (positive and negative) and activated DR (also in both directions) are included in the formulation

$$\mathrm{EP}_{s,w} = \sum_t \lambda_{t,s}*w_t + \lambda_{t,s}^+*\sigma_{t,w}^+ - \lambda_{t,s}^-*\sigma_{t,w}^- - \mathrm{dr}_{t,w}^+*y_t^+ - \mathrm{dr}_{t,w}^-*y_t^- - \left(\mathrm{DR}_t^+ + \mathrm{DR}_t^-\right)*c. \quad (2)$$

The proposed formulation is bounded by the set of constraints (3)–(5) and (7)–(30). CVaR in (3) is calculated based on scenario-dependent costs in order to obtain an adequate Gaussian distribution and is a coherent risk measure, since it can be expressed using a linear formulation. In (4), variable $\mathrm{EP}_{s,w}$ represents the expected profit in scenarios s and w and η_{sw} is an auxiliary variable whose value is equal to zero if scenario w has a total cost lower than VaR. Note that $\eta_{s,w}$ is equal to the difference between the corresponding profit and VaR for any scenario (5). The inclusion of the weighted correction factor β underlines the balance between risk and expected costs. The value of β varies from 0 to 1

$$\mathrm{CVaR} = \mathrm{VaR} - \frac{1}{1-\alpha}\sum_{w,s} \xi_w * \xi_s * \eta_{s,w} \quad (3)$$

$$\mathrm{VaR} - \mathrm{EP}_{s,w} - \eta_{s,w} \leq 0 \quad (4)$$

$$\eta_{s,w} \geq 0. \quad (5)$$

Positive and negative load shifting limits for each hour and scenario, based on the aforementioned concept of elasticity of substitution, are determined in (6). The slope of the function is determined by the price elasticity assumptions, including both own- and cross-price elasticities. Since the DR aggregator participating in a price-based DR program is considered, the willingness to modify the foreseen consumption pattern depends on the price difference observed in the day-ahead market. A weighted average of the demand is considered to guarantee symmetry in both ways

$$\mathrm{DR}_{t,s} = \sum_{t1} \varepsilon_{t,t1} * \left(\frac{d_t + d_{t1}}{2}\right) * \left(\frac{\zeta^+_{t,s} + \zeta^-_{t,s}}{\bar{\lambda}_{t,s}}\right) \; \forall t \neq t1. \quad (6)$$

Constraints (7) and (8) guarantee the level of contracted DR in both directions for each hour is below the weighted average of the limits considered (6). Contracted positive and negative DR cannot be higher than the available DR. Constraints (9)–(12) guarantee the level of activated DR is below the contracted DR for every timeslot and wind and price scenario

$$\mathrm{DR}^+_t \leq \sum_s \xi_s * \mathrm{DR}_{t,s} \quad (7)$$

$$\mathrm{DR}^-_t \leq \sum_s \xi_s * \mathrm{DR}_{t,s} \quad (8)$$

$$0 \leq \mathrm{dr}^+_{t,w} \leq \mathrm{DR}^+_t \quad (9)$$

$$0 \leq \mathrm{dr}^-_{t,w} \leq \mathrm{DR}^-_t. \quad (10)$$

The concept of deviation refers to the difference between the wind offer and the forecasted power production scenario. In order to account for positive and negative deviations, an additional binary variable has been introduced in the model description. The formulation of positive and negative deviations is presented

$$\rho^+_{t,w} = n_{t,w} * (wf_{t,w} - w_t) \quad (11)$$

$$\rho^-_{t,w} = (1 - n_{t,w}) * (w_t - wf_{t,w}) \quad (12)$$

$$\rho^+_{t,w} \geq 0 \quad (13)$$

$$\rho^-_{t,w} \geq 0. \quad (14)$$

Imbalance refers to the final deviation once the contracted DR has been activated. The mathematical formulation of the imbalance is presented

$$\sigma^+_{t,w} = \rho^+_{t,w} - \mathrm{dr}^+_{t,w} \quad (15)$$

$$\sigma^-_{t,w} = \rho^-_{t,w} - \mathrm{dr}^-_{t,w}. \quad (16)$$

Positive and negative price deviations in the day-ahead market are presented in (17) and (18). Expected day-ahead price outcomes and price deviations are relevant for both, direct revenues of wind power offering and expected costs and revenues associated to load shifting from DR

$$\zeta^+_{t,s} = \upsilon_{t,s} * \left(\lambda_{t,s} - \bar{\lambda}\right) \quad (17)$$

$$\zeta^-_{t,s} = (1 - \upsilon_{t,s}) * \left(\bar{\lambda} - \lambda_{t,s}\right). \quad (18)$$

The costs associated to DR shifting to higher price hours, and the benefits linked to DR shifting to lower price hours are guaranteed in the problem formulation (19) by the contracted power, independent from their final utilization. The first term of the inequality represents the payment to the DR aggregator by the WPP, while the second one represents the expected costs and incomes associated to DR shifting in the market. Equation (19) determines the DR price for the bilateral agreement that guarantees DR aggregator the association with WPP is beneficial, getting at least the benefit it would obtain in day-ahead market for its flexibility

$$\sum_t \left(\left(\mathrm{DR}^+_t + \mathrm{DR}^-_t\right) * c\right) \geq \sum_{t,s} \Big(\xi_s * \mathrm{DR}^+_t * \zeta^+_{t,s} + \xi_s * \mathrm{DR}^-_t * \zeta^-_{t,s}\Big). \quad (19)$$

Contracted positive and negative DR volumes are linked by the own-price elasticity, as per (20). Expected daily consumption of the aggregator varies within a range dependent on own-price elasticity, since cross-price elasticity accounts for load-shifting strategies

$$\sum_t \mathrm{DR}^+_t \geq \sum_t \mathrm{DR}^-_t - \sum_{t,s} \xi_s * \varepsilon_{t,t} * d_t * \left(\frac{\zeta^+_{t,s} - \zeta^-_{t,s}}{\bar{\lambda}_{t,s}}\right). \quad (20)$$

Equation (21) represents the average price for the day-ahead market and the prices associated to positive and negative imbalances are defined in (22) and (23). Increasing the factors for positive deviations or reducing the values for negative deviations reduces the profitability of the joint bidding strategy. On the contrary, reducing the factors for positive deviations or increasing the values for negative deviations results in a higher value of the contracted DR. The values in (22) and (23) are consistent with those proposed in [11]

$$\bar{\lambda} = \sum_{t,s} \frac{\lambda_{t,s}}{T} \quad (21)$$

$$\lambda^+_{t,s} = 0.9 * \lambda_{t,s} \quad (22)$$

$$\lambda^-_{t,s} = 1.1 * \lambda_{t,s} \quad (23)$$

$$\forall t \in \Omega^t, w \in \Omega^w, i \in {\Omega^n}_i, j \in {\Omega^n}_j, z \in {\Omega^n}_z, (n, np) \in \Omega^l.$$

Finally, nonlinear terms appear in the problem formulation. They are of the type (binary variable) × (continuous variable) or (continuous variable) × (continuous variable). The linearization procedure is shown in Section II-C.

C. Linearization

As mentioned before, optimal bidding strategy variables are discretized to a finite set of values. To do this, a binary expansion approach [16] has been used. Then, the discrete positive DR contracted variable, DR_t^+, is defined by 2^k steps (or blocks) between DR_t^{0+} and $\mathrm{DR}_t^{\max+}$ with $\Delta\mathrm{DR}_t^+$ distance between two consecutive values of DR_t^+ by adding binary variable $\kappa_{k,t}$ (24). A similar procedure has been followed for the linearization of the discrete positive DR contracted variable, DR_t^- in (25)

$$\mathrm{DR}_t^+ = \mathrm{DR}_t^{0+} + \Delta\mathrm{DR}_t^+ * \sum_k 2^k * \kappa_{k,t} \tag{24}$$

$$\mathrm{DR}_t^- = \mathrm{DR}_t^{0-} + \Delta\mathrm{DR}_t^- * \sum_k 2^k * \partial_{k,t}. \tag{25}$$

Then, the equivalent integer linear reformulation (also known as Fortuny-Amat and McCarl reformulation [17]) is defined in (26)–(29). Nonlinear terms associated with the product of binary and continuous variables (26) are discretized to a finite set of values

$$\theta_{t,w} = \mathrm{bin}_{t,w} * \mathrm{var}_{t,w} \mathrm{bin} \in \{0, 1\},\ \mathrm{var} \in \left\{\mathrm{var}^{\min}, \mathrm{var}^{\max}\right\}. \tag{26}$$

The nonlinear product of binary and continuous variables can be equivalently reformulated as an integer linear set of equations (also known as Big-M reformulation) (27)–(29). An auxiliary variable, r, is included in the reformulation

$$\theta_{t,w} = \mathrm{var}_{t,w} - r \tag{27}$$

$$\mathrm{bin}_{t,w} * \mathrm{var}^{\min} \le \mathrm{var}_{t,w} - r \le \mathrm{bin}_{t,w} * \mathrm{var}^{\max} \tag{28}$$

$$(1 - \mathrm{bin}_{t,w}) * \mathrm{var}^{\min} \le r \le (1 - \mathrm{bin}_{t,w}) * \mathrm{var}^{\max} \tag{29}$$

$$\mathrm{bin} \in \{0, 1\},\ \mathrm{var} \in \left\{\mathrm{var}^{\min}, \mathrm{var}^{\max}\right\},\ r \in \left\{\mathrm{var}^{\min}, \mathrm{var}^{\max}\right\}.$$

The lower limit of the continuous variables considered in the problem formulation is zero, simplifying the expressions described above ($\mathrm{var}^{\min} = 0$).

III. Numerical Results

A. Case Study

In order to illustrate the accuracy of the model, some numerical studies are performed. To test the feasibility of the proposed methodology, a case study of a hypothetical wind farm and a DR aggregator is presented. A case study consisting of a 7-MW wind farm is considered. The demand aggregator considered in the proposed formulation aggregates up to 7 MW at the peak hour (hour 21). Profiles for wind power scenarios and aggregated demand are presented in Figs. 1 and 2. Each scenario is composed of a combination of day-ahead price and wind forecasts. Ten scenarios have been considered for wind and day-ahead price forecasts, resulting in a total number of hundred scenarios after its combination.

Price data used for the scenario generation process for day-ahead prices are presented in Fig. 3. In order to account for the uncertainty around the true outcomes of day-ahead prices and wind power, CVaR has been used. A Monte Carlo simulation has been used to generate a sufficient number of wind and day-ahead price scenarios. Obtained scenarios have been used to calculate the optimal profit distribution with a 95% confidence level of CVaR, where the WPP risk aversion is represented by $\beta \in (0, 1)$, which is tabulated to vary within this range. Numerical results illustrate how the proposed bidding strategy for wind and DR pairing increases the expected benefit of both resources and reduces the related risk. Positive and negative imbalance prices have been considered in the problem formulation as dependent on day-ahead market prices, as outlined in (22) and (23). The positive and negative activated DR prices are €0.1/MWh.

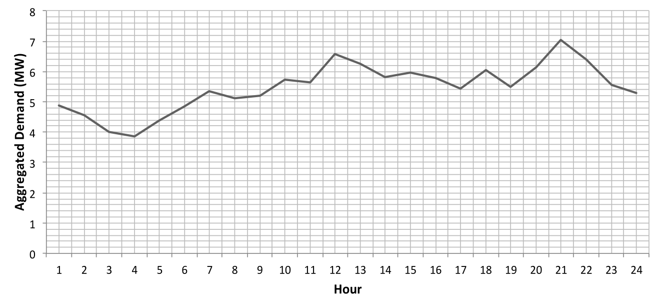

Fig. 1. Aggregated demand (d_t).

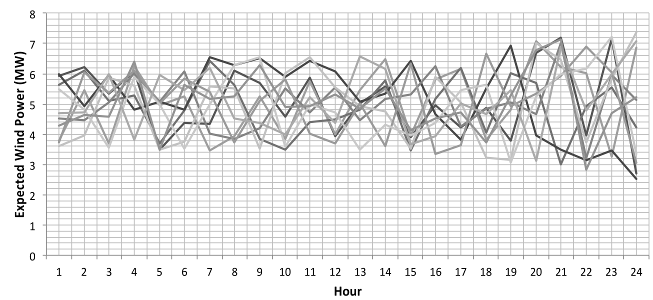

Fig. 2. Expected wind power ($wf_{t,w}$).

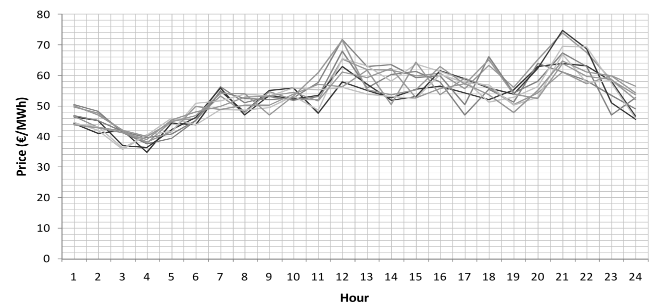

Fig. 3. Day-ahead price scenarios ($\lambda_{t,s}$).

B. Numerical Results

The optimal amount of the power bid in each hour in the day-ahead market for the WPP disregarding DR is shown in Fig. 4. The bidding strategy highly depends on the considered risk aversion, as can be observed in the figure, especially for hours 5, 13, and 22.

The results for the optimal bidding strategy including DR in the model formulation are shown in Fig. 5. Including DR in the day-ahead bidding strategy results in a higher expected

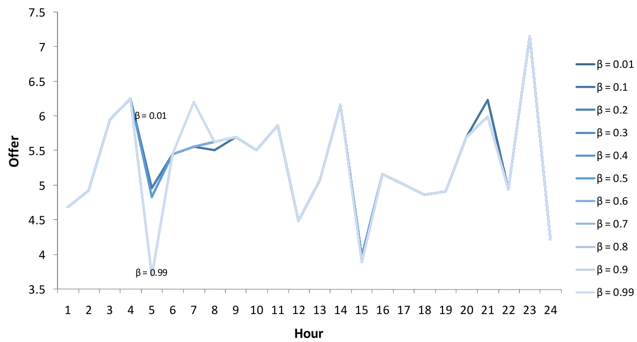

Fig. 4. Bidding strategy without DR (w_t).

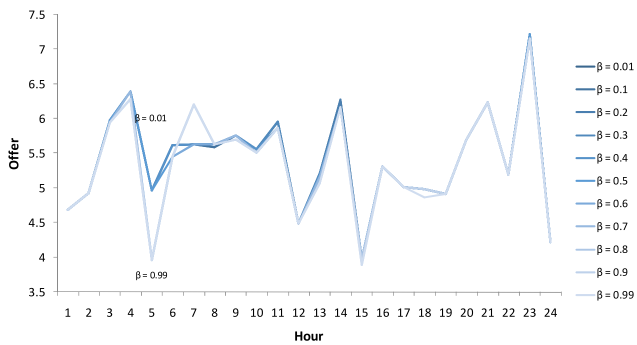

Fig. 5. Bidding strategy with DR (w_t).

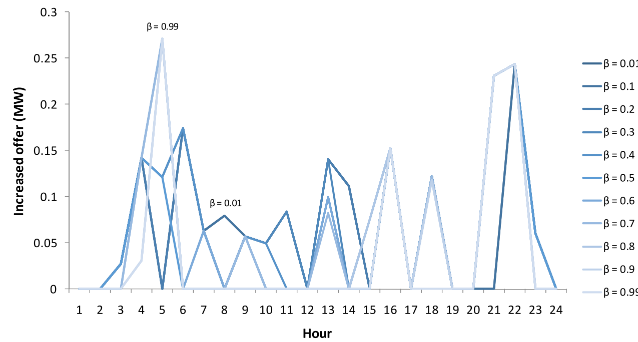

Fig. 6. Increased bid considering DR.

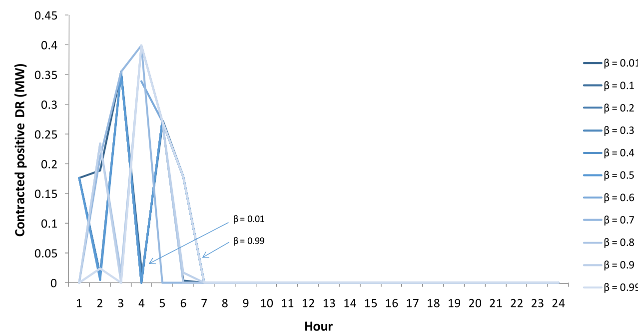

Fig. 7. Contracted positive DR (DR_t^+).

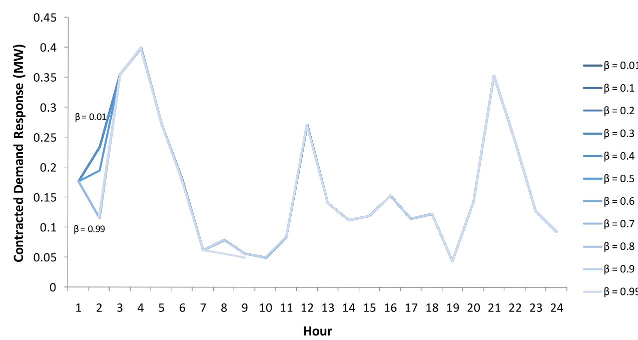

Fig. 8. Contracted negative DR (DR_t^-).

profit for the WPP, guaranteeing at the same time the recovery of the costs associated to DR shifting to higher price hours, and the benefits linked to DR shifting to lower price hours for the DR aggregator. Jointly considering WPP and the DR aggregator in the bidding process results in a higher volume of wind offered in the day-ahead market, increasing the penetration of renewable technologies. Thus, a combined WPP and DR offer is profitable for both counterparties, reduces imbalances, and facilitate the integration of renewable technologies. The difference between both bidding strategies is presented in Fig. 6.

This paper considers a conservative value of 1% in each of the daily hours for cross-price elasticity as adequate. The elasticity of substitution between two different hours is constant no matter the considered hours, being susceptible of a finer tuning once the required technology is in place. Own-price elasticities of demand of 7.5% is tested, inspired by [12]. However, the scope of this paper is not the analysis of consumer's preferences but the implementation of an aggregated bidding strategy.

The contracted DR is partially used to increase the WPP offer in the day-ahead market. Comparing the results obtained in Figs. 4 and 5, the increased bid (bid with DR in Fig. 5 minus bid without DR in Fig. 4) is presented in Fig. 8. It can be observed how the lower the risk aversion of the WPP is, the higher the level of contracted DR. The deviations resulting from the difference between the offer and the final WPP production are reduced through the incorporation of DR in the WPP bid, increasing the expected profit of the WPP.

As described in the model formulation, DR can be contracted in both directions, covering positive and negative imbalances. Results for both positive and negative contracted DR are presented in Figs. 7 and 8. It can be observed how positive and negative DR is contracted for the first 7 h. Positive DR is contracted in the first hours since they correspond to lower price hours and a certain amount of positive DR is required by (20). Contracted negative DR corresponds to high-deviation scenarios, as per hours 5, 13, and 22.

Numerical results in the case of the WPP optimal bid disregarding DR are presented in Table I.

The expected profit versus CVaR is presented in Fig. 9. A confidence level of 95% is used to compute CVaR in all instances. There are 11 points arising from the solution of the maximization problem described in (1)–(29) by modifying parameter β. This parameter models the tradeoff between the expected profit and the profit variability (measured in terms of CVaR). The first point is obtained solving the problem with a near-zero β parameter. The point represents the maximum

TABLE I
RISK VERSUS EXPECTED PROFIT (WITHOUT DR)

α	β	*Expected Profit [€]*	*VaR[€]*	*CVaR[€]*
0.95	≈ 0	6317.369	6082.435	6029.532
0.95	0.1	6317.369	6082.435	6029.532
0.95	0.2	6316.936	6084.578	6031.636
0.95	0.3	6316.831	6085.130	6031.949
0.95	0.4	6316.831	6085.130	6031.949
0.95	0.5	6316.831	6085.130	6031.949
0.95	0.6	6315.755	6079.868	6032.982
0.95	0.7	6314.402	6076.734	6033.644
0.95	0.8	6314.402	6076.734	6033.644
0.95	0.9	6314.402	6076.734	6033.644
0.95	≈ 1	6314.402	6076.734	6033.644

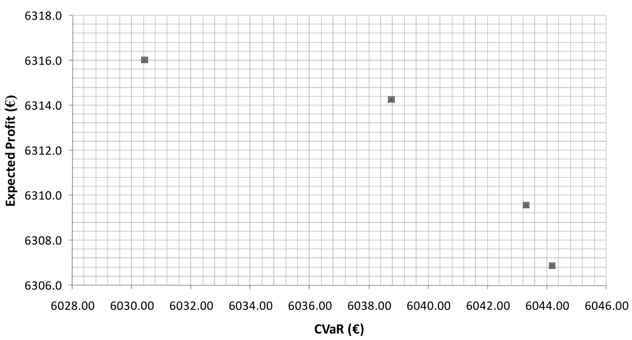

Fig. 9. Efficient frontier without DR.

TABLE II
RISK VERSUS EXPECTED PROFIT (WITH DR)

α	β	*Expected Profit [€]*	*VaR[€]*	*CVaR[€]*
0.95	≈ 0	6427.20	6175.78	6175.78
0.95	0.1	6427.20	6175.78	6175.78
0.95	0.2	6427.03	6176.65	6176.65
0.95	0.3	6426.27	6178.90	6178.90
0.95	0.4	6424.89	6181.82	6181.82
0.95	0.5	6420.95	6187.71	6187.71
0.95	0.6	6413.01	6200.74	6200.74
0.95	0.7	6412.37	6201.16	6201.16
0.95	0.8	6384.74	6213.69	6213.69
0.95	0.9	6382.49	6215.62	6215.62
0.95	≈ 1	6354.30	6219.63	6219.63

profit but at the minimum CVaR ($\beta \approx 0$). As per (1), numerical results for $\beta \approx 0$ are equivalent to the stochastic optimal bidding strategy without CVaR. It can be observed from the figure that the higher the risk aversion, the lower the expected profit is, resulting in a more conservative offer.

Table II presents the numerical results of the expected profit for WPP when considering the aggregation of wind and DR in the offer. The proposed methodology results in a significant increase in the expected outcomes for the WPP of circa 2%, guaranteeing at the same time the recovery of all relevant costs by the DR aggregator. Furthermore, additional flexibility not considered in the direct trading of DR in electric

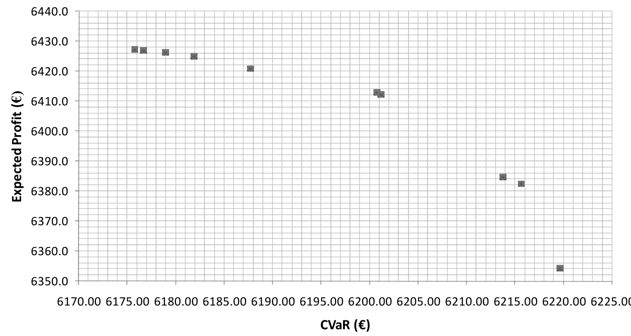

Fig. 10. Efficient frontier considering DR.

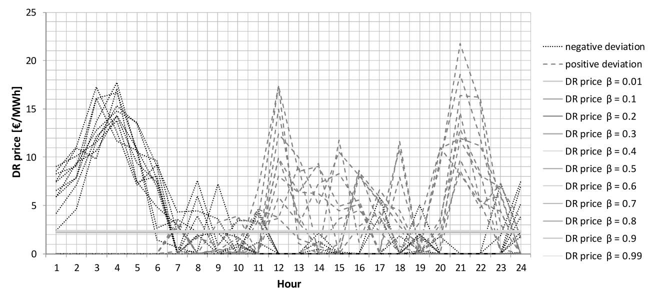

Fig. 11. Positive and negative contracted DR prices and day-ahead deviations.

power systems under real time pricing has been revealed by the proposed methodology, increasing the value of DR.

The expected profit versus CVaR considering the aggregation of wind and DR is presented in Fig. 10. A confidence level of 95% is used to compute CVaR in all instances.

According to the numerical values provided, the considered joint bidding strategy results in a significant increase in expected outcomes for WPP of circa 2%, guaranteeing at the same time the DR a better compensation for its flexibility than the one obtained in the day-ahead market. The price for the DR contract is defined as an endogenous variable of the model formulation. The results presented in Fig. 11 present the cost of contracting DR for each parameter β with a confidence level of 95%. DR prices for the bilateral agreement are almost identical, roughly €2.3/MWh, revealing the value of flexibility for WPP. In Fig. 11, DR prices represent the values obtained for c, while positive and negative price deviations refer to $\zeta_{t,s}^{+}$ and $\zeta_{t,s}^{-}$, respectively.

Simulations have been implemented on a Dell PowerEdge R910X64 with 4 Intel Xeon E7520 processors at 8 GHz and 32 GB of RAM using CPLEX 12.6 [18] under GAMS 24.2.3 [19]. CPLEX requires around 70 seconds for the eleven iterations required for parameter β, ranging from 0.01 to 0.99. The CPU time does not depend on the value of parameter β.

IV. CONCLUSION

The benefits of the proposed pairing methodology for wind and DR in the day-ahead market through bilateral contracts have been outlined in this paper. Additionally, the aggregation of both technologies reveals a further flexibility for DR not considered when offering directly to the day-ahead market. The problem formulation results in a significant increase in the expected outcomes for WPP of circa 2%, guaranteeing at the same time the recovery of all relevant costs and expected profits by the DR aggregator. The price settlement for the bilateral contract between wind and DR is considered endogenous to the problem. Furthermore, imbalances due to the stochastic nature of renewable technologies are lowered as a direct consequence of the pairing strategy, benefiting both WPPs and the system operator. Numerical results showing the potential benefits of wind and DR are provided, validating the proposed approach.

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