

Risk-Constrained Offering Strategy for Aggregated Hybrid Power Plant Including Wind Power Producer and Demand Response Provider

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Abstract—The unpredictable and volatile nature of wind power is the main obstacle of this generation source in short-term trading. Owing to the ability of demand side to cover wind power imbalances, aggregated loads have been presented in the literature as a good complementary resource for the wind generation. To this end, this paper proposes a technique to obtain the best offering strategy for a hybrid power plant consisting of a wind power producer and a demand response provider in the power market. In addition, conditional value-at-risk is used to limit the risk on profit variability. Finally, a detailed analysis of a realistic case study based on a wind farm in Spain has illustrated that joint operation of wind power producers and demand response providers can increase the expected profit and reduce the potential risks.

Index Terms—Hybrid power plant, wind power, demand response, offering strategy, stochastic programming.

NOMENCLATURE

The main notation of the paper is expressed below for quick reference. The other symbols are described as required.

A. Indices and Numbers

t (T) Index (set) for hourly periods.
 ω (Ω) Index (set) for scenarios.

B. Parameters

W^{\max} Wind farm capacity (in MWh).
 α Confidence level.
 β Risk-aversion parameter.

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ϑ^* Fixed rate for each MW load reduction (in €/MWh).
 μ Maximum percent of the load did not need to be recovered.
 σ Factor which define relation of elasticity and price.
 η_1, η_2 Upper and Lower bound of demand response.
 D_{0t} Normal demand level in period t (in MWh).
 γ Lower bound for offering to the intra-day market.
 ρ_ω Occurrence probability of scenario ω .

C. Random Variables

$W_{t\omega}$ Wind power in period t and scenario ω (in MWh).
 $\vartheta_{t\omega}^D, \vartheta_{t\omega}^I$ Day-ahead and intra-day market price (in €/MWh).
 $\vartheta_{t\omega}^+, \vartheta_{t\omega}^-$ Positive/negative imbalances' price (in €/MWh).
 $R_{t\omega}^+, R_{t\omega}^-$ Positive/Negative imbalance ratios.
 SCN Scenario.

D. Continuous Variable

$P_{t\omega}^D$ Day-ahead offer of wind power producers (in MWh).
 $P_{t\omega}^I$ Intra-day offer of wind power producers (in MWh).
 $P_{t\omega}^{\text{sch}}$ Scheduled power of wind power producer (in MWh).
 $\delta_{t\omega}$ Total deviation of wind power producer from the scheduled power (in MWh).
 $\delta_{t\omega}^+, \delta_{t\omega}^-$ Positive/Negative deviation of wind power producer from the scheduled power (in MWh).
 $P_{t\omega}^{D,\text{hpp}}$ Day-ahead offer of hybrid power plant (in MWh).
 $P_{t\omega}^{I,\text{hpp}}$ Intra-day offer of hybrid power plant (in MWh).
 $P_{t\omega}^{\text{sch, hpp}}$ Scheduled power of hybrid power plant aggregator (in MWh).
 $\delta_{t\omega}^{+,\text{hpp}}, \delta_{t\omega}^{-,\text{hpp}}$ Positive/Negative deviation of hybrid power plant from the scheduled power (in MWh).
 $\delta_{t\omega}^{\text{hpp}}$ Total deviation of hybrid power plant from the scheduled power (in MWh).
 L_t^D Value of load reduction which offer to the day-ahead market in period t (in MWh).

L_{tw}^I	Value of load reduction which offer to the ID market (in MWh).
L_{tw}^{sch}	Demand side scheduled power (in MWh).
ξ	Expected profit (€).
z_ω	Auxiliary variable for calculating Conditional Value-at-Risk in scenario ω .
var	Auxiliary variable for calculating conditional value-at-risk.

E. Function

$\mathbb{E} [\cdot]$	Function to calculate the expected value by using the summation of multiplied value obtained from each scenario and the occurrence probability of the related scenario.
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I. INTRODUCTION

A. Aims and Scope

DUE to the environmental concerns and the fossil fuel crisis, renewable energy resources (RERs) are increasing at a rapid rate in many electricity systems throughout the world. It is predicted that the share of the generation of RERs will be more than 25% of the world's electricity until 2035, of which a quarter will be generated by the wind energy resources [1], [2].

Restructuring of power industry poses a competitive environment with private players. Because of the uncertain, volatile and undispachable nature of the wind generation, wind power producers (WPPs) can barely compete with conventional power producers in the electricity market. Supporting schemes which are based on the market such as fixed feed in-tariff and feed in-tariff premium, i.e., a low and high limit that guarantees minimum and maximum tariffs irrespective of the electricity market prices, and non-market support schemes such as government subsidies and tax exemption are different mechanisms that are proposed and implemented for supporting WPPs in various countries all over the world [3].

With respect to the improvement and growth of wind generation technologies and due to the nowadays tariff deficit and negative economic conjunctures, supporting schemes mentioned above are gradually becoming less and less relevant. These circumstances increase WPPs' tendency to participate in the electricity market to maximize their profit [4]. However, WPPs face two main uncertain sources: wind power production and market prices. Significant fluctuation of the wind production and considerable uncertainty of prices cause major variability and loss on WPPs profit. It is due to the fact that WPPs are responsible for their energy deviations (difference between the scheduled and actual production) which must be covered in imbalance mechanism provided by expensive sources. Therefore, it is absolutely crucial to develop an innovative and practical short term offering strategy for WPPs and enable them to hedge against these uncertainties.

B. Background and Approach

The publications in the area are generally classified into *two* main approaches:

Firstly, numerous studies have attempted to provide and improve an optimal offering strategy model for participation of WPPs in the electricity market by themselves with respect to the various market infrastructures and rules [4]–[8].

Secondly, other technologies, facilities, options and programs have been coordinated with WPPs in order to mitigate the randomized behavior of the wind generation. Financial options have been introduced to handle WPPs uncertainties in [9]. Utilizing other technologies and facilities such as storage devices [10], pumped-storage hydro plants [11], gas turbines and compressed air energy storage [12] as supplemental energy resources beside the wind farms are various solutions proposed in the literature to reduce the variability and uncertainty in the net output of the joint scheme of these facilities and wind generators. Although, the storage can reduce the imbalance cost stemmed from wind power fluctuations, the current high investment cost of the storage makes it an uneconomic solution. In recent years, it has been suggested that demand response (DR) resources can be a flexible and cost-effective option to handle the variability of WPPs [13]. Several publications have been appeared in recent years, studying the effect of DR program for the wind power generation from different points of view [14]–[17]. In this regard, reference [14] proposes an approach to determine the proper value of the load shifting from off-peak to peak from ISO's viewpoint and under the ISO's direct load control for improving the utilization of wind generation. Reference [15] utilizes the critical peak pricing, which is one of the DR programs, from the view point of load serving entity that has wind energy to sell to the day-ahead (DA) market and investigates the optimal value of the critical peak pricing. Reference [16] assesses the impacts of DR resources as an alternative to manage the voltage profile. In [17], the author evaluates the effect of market design and rules as well as DR programs on reducing the impact of wind power forecast errors. Nevertheless, a few researchers have investigated the positive benefits of DR on the WPPs short term trading from the WPPs' viewpoint [18], [19]. Reference [19] has proposed a platform for trading DRRs in a separate intra-day (ID) market in order to improve the WPPs' profit. Then the model has been solved from WPPs' point of view. In this situation, which the profit of demand side (DS) is not considered and discussed, one question arises: *How can the demand response provider (DRP) be convinced and motivated to collaborate with WPPs in such a market?* In that paper, a separate market named intra-day demand response exchange market is considered instead of conventional ID market for trading DR between DR providers and DR users. Under this assumption, another question which bears in mind is that: *Who is responsible for the cost and the process of procuring that market and how the signal of it can affect the conventional ID market in the same time?* In [19], the operation of WPPs and flexible loads in the DA market has been analyzed. Reference [19] has totally ignored the *uncertainties* related to the power market prices and has supposed the market prices as the deterministic values and also the *risk* related to the problem is not considered. It also obtain only simple *offering quantity* and not *offering curves*. In addition, the ID market which is specially good for renewable energy resources and specifically for WPPs is not considered in it.

The current paper focuses on the second approach and evaluates the effectiveness of the joint operation (JO) of the loads with an existing wind farm, to form a hybrid wind-DR power plant. Indeed, in this context, a hybrid power plant (HPP) of wind farm that uses flexible loads as a storage device is considered. This paper considers the DR beside the wind power simultaneously in the both DA and ID markets which has not been proposed in the literature yet. We consider the related *uncertainties*, i.e., wind production, DA market prices, ID market prices, and balancing market prices, in the form of scenarios. Then, a three-stage stochastic programming model is developed to obtain the optimal offering strategy for the JO of WPP and DRP in the form of simple *generation bids* or even *offering curves* and also compare it with uncoordinated operation (UO) of them to assess the benefits of the proposed method. A risk measure tool is also employed to manage the risk of the problem.

C. Contribution

To the best of our knowledge, the main contributions of this paper with respect to the current literature in the area can be summarized as follows:

- The development of a two-stage stochastic decision making model for participation of DR in the both DA and ID competitive market.
- The development of an optimal offering strategy model for the JO of a WPP and a DRP to maximize their expected profit and control their risk to mitigate wind power uncertainties.
- The development of a method to generate the scenarios and proposing a simple way to consider the correlation between the stochastic variables.
- The implementation and analysis of the proposed framework on a realistic case study.

D. Paper Framework

The remainder of the paper is organized as follows: section II presents a detailed description of the problem. Section III provides uncertainty characterization. Next, the mathematical formulation of the problem is described in Section IV. Section V provides results for a realistic case study. Section VI draws conclusions.

II. PROBLEM DESCRIPTION

A. Market Framework

This paper considers a bi-directional multimarket including three trading floors, shown in Fig. 1, as described below:

1) *DA Market*: In order to participate in the DA market of day D+1 all the producers/consumers have to submit their sales/purchases offer to the Market Operator (MO) before 10:00 A.M. of day D. Then, the Market Clearing Price (MCP) can be derived through the conjunction of the supply and demand curve.

2) *Intra-Day Market*: Due to the wide time horizon between the closure of DA market and delivery time (14 hours

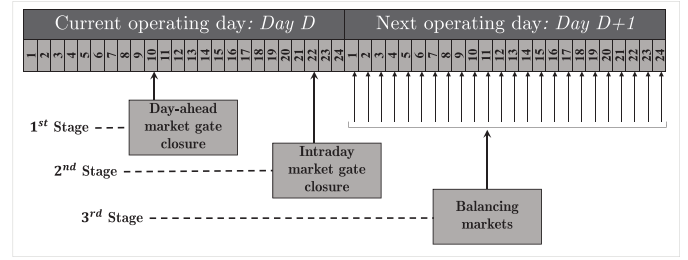


Fig. 1. Market framework.

in this case), after the closure of DA market, an adjustment market may assist the participants to modify their offers. In this trading floor, the producers can submit both purchase and sales offers in order to correct their offers and react to the latest information that is gained during the closure of DA market and ID market. This trading floor is especially good for the producers which are faced with uncertainty, e.g., WPPs. It should be noted that this paper considers one adjustment market, i.e., ID market, which remains open until $2\frac{1}{4}$ hours before real time generation as shown in Fig. 1.

3) *Balancing Market*: Balancing markets, which are open until 15 minutes before the real time, allows producers to cover their imbalances. In fact, this trading floor guarantees the continuous balance between electricity production and consumption. It should be noted that the imbalances may be positive (higher generation) or negative (lower generation). According to the total imbalances of the system, a dual-price balancing market is considered in this context. The mechanism of the imbalance prices has been extracted from [4].

B. Demand Side Modeling

Most consumers do not have the means to participate directly in the power markets. Therefore, they need the services of an aggregator in order to participate in these markets. Aggregation service providers are therefore central players in the creation of a vital DR program and demand side's (DS's) participation in the power market. The main function of aggregation is to determine and gather the flexibilities of the consumers to build DR services.

DR seeks a shifting of load from on-peak to off-peak and possibly a decrease in total load in response to time-based rates or other forms of financial incentives. The DS contains a large number of loads which can be categorized into three main groups according to their flexibility:

- A part of loads is neither flexible to be shifted in time nor to be deleted.
- A part of loads is flexible to shift back or forward in time.
- A part of loads can be deleted and does not need to be recovered.

In order to accommodate DR in the power markets, load control and demand side load management programs have been designed and implemented in many competitive power markets. These programs usually include a set of ISO-based programs which permitted the demand side to provide *interruptible loads*

as a commodity in the power market. For instance, New York independent system operator utilizes DA demand response program where the DS can offer the hourly load reduction in DA market. If their offer is accepted, they will receive DA Locational Based Marginal Price in addition to an incentive based on the real time operation [20]. Because of the better prediction after DA gate closure, DR also can be traded in an ID market. For instance, California independent system operator has designed participating load program to integrate DS in the wholesale market. It includes non-spinning reserve and replacement reserve which allows loads to participate in the DA and ID markets to offer their load reduction. It should be mentioned that, under these programs, loads are only permitted to bid their reduction and they are treated in the same manner as generators with respect to scheduling. If their offer is accepted, they will be given a capacity payment in addition to an energy payment based on the real time operation [21].

In order to develop an economic model for the participation of DS in the power market, we assume that DR can be traded in both DA and ID market and it is only allowed to bid its reduction in the same manner as generators offer their production. It should be mentioned that in the proposed framework they will be awarded an energy payment in addition to an incentive for load reduction provided that their offer is accepted. As it will be explained later, the value of the incentive depends on the time horizon (low demand period, off peak period and peak period), Market Clearing Price (MCP) and load curves.

C. Operation of an HPP in the Market

In the proposed platform, WPP and DRP act as a coordinated unit. JO of WPP and DRP is more flexible and less risky than independent operation. Indeed, the benefits of this scheme are twofold.

- 1) WPP can utilize DR to cover its uncertainty and mitigate the imbalance cost.
- 2) DR can profit from reducing its consumption during peak period and recovering it by wind energy in the off-peak period.

As it can be seen in Fig. 2, in the UO, WPPs submit their generation offer and the DRPs submit their reduction bid independently. According to the proposed scheme, for the JO of WPP and DRP a central planner/manager is required. The so called *HPP* aggregator is directly responsible for participating in the power market. Accordingly, firstly, *HPP* aggregator gathers the information of WPP (e.g., predicted wind power) and DRP (e.g., load shifting/reduction capability, initial hourly load) and afterwards, devises the best offering strategy by predicting market prices and based on the latest information, technical constraints and market rules.

III. UNCERTAINTY CHARACTERIZATION

A. Stochastic Programming Approach

As it was discussed in the previous section, WPPs face two major sources of uncertainty: availability of the wind generation and market prices (DA, ID and balancing). In addition, DRP problem described above is subject to the uncertainty of DA

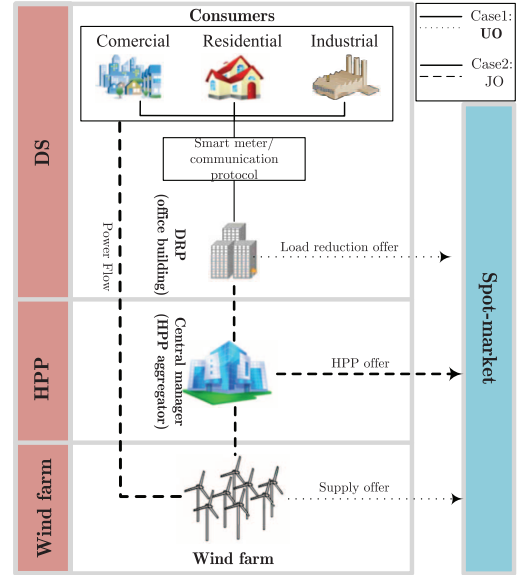


Fig. 2. Schematic representation of the proposed configuration.

and ID market prices. In order to deal with the adverse financial effect of these uncertainties on the WPP and DRP offer, they have been modeled as stochastic processes. To this end, a multi-stage stochastic programming is employed to solve WPP and DRP problem. Note that, each stage indicates a trading floor. Therefore, the decision variables are accordingly classified as the first-stage (*here-and-now*), second-stage (*wait-and-see1*) and third-stage (*wait-and-see2*) decision variables. The process of decision making and the decision variables pertained to each stage is described below.

- 1) First-stage (Ω_1): Decision making of the first stage should be done before the realization of the stochastic process becomes available and it should be independent of scenarios. As mentioned above, the first-stage decision variables are related to the DA market (P_{tw}^D, L_t^D).
- 2) Second-stage (Ω_2): While the DA market prices are known for each time horizon, the decision variables of this stage (*wait-and-see1*) are feasible for every possible realization of DA market prices. $P_{tw}^I, L_{tw}^I, P_{tw}^{sch}$ are decision variables of the second-stage.
- 3) Third-stage (Ω_3): Decision variables of the third and last stage of the stochastic programming pertain to the balancing market. These decision variables ($\delta_{tw}^-, \delta_{tw}^+$) are made after the whole stochastic variables are observed. Note that, the decision variables of the third-stage are feasible for each plausible realization of scenarios.

B. Scenario Generation

Stochastic variables of the problem, i.e., wind power and market prices, are characterized by a set of discrete scenarios. A hybrid intelligent model composed of a modified hybrid neural network (MHNN) and enhanced particle swarm optimization (EPSO) ([22], [23]) is used in this paper to generate scenarios for each stochastic variable independently. The process of scenario generation for wind power is described below. It should be mentioned that the scenarios are generated in the same manner for the other stochastic variables.

- 1) Firstly, predict the wind power output for 30 days before the offering day, and calculate prediction errors for each hour of related days. With respect to the hourly prediction errors, the probability distribution function (PDF) of wind power forecast error should be estimated for each hour (in this case 24 PDF).
- 2) Next, by predicting the wind power for offering day, and according to the hourly PDF of error in the preceding step a large number of scenarios are generated using roulette wheel mechanism [24].
- 3) Finally a scenario reduction method is employed to reduce the number of scenarios. Reference [25] proposes two different scenario reduction techniques based on Kontorovich distance. A fast forward selection algorithm is used for diminishing the number of scenarios in this paper.

In order to consider the correlation among the market prices, instead of modeling ID and balancing market prices, $(\vartheta^D - \vartheta^I)$ and $(R^+ + R^- - 1)$ are modeled through scenarios, respectively. This is a simple way to consider such correlation. The correlation between market prices and wind power require

Algorithm 1. Process of scenario generation

Require: Historical data and parameters as follows:

- Historical data related to *wind power production* (e.g., wind speed, temperature, pressure).
- Historical data related to *DA, ID and balancing (positive and negative) market prices*.
- Number of scenarios in the initial and reduced scenario sets for the wind power production (N_1), DA market prices (N_2), ID market prices (N_3) and balancing market prices (N_4).

- 1: Construct the time series related to *i*) the wind power production, *ii*) DA market prices (ϑ^D), *iii*) the differences between the ID and DA market prices ($\Delta\vartheta^I = \vartheta^D - \vartheta^I$) and, *iv*) the balancing market ratio¹ ($R = R^+ + R^- - 1$) for training the neural network.
- 2: Utilize the three-step approach which has been described in section III-B to characterize:
 - N_1 scenarios for the wind power production (W);
 - N_2 scenarios for DA market prices (ϑ^D);
 - N_3 scenarios for the differences between the ID and DA market prices ($\Delta\vartheta^I = \vartheta^D - \vartheta^I$);
 - N_4 scenarios for the balancing market ratio ($R = R^+ + R^- - 1$).

¹Note that the imbalance market ratios are suitable for those markets which very occasionally zero prices occur. For those markets which zero prices may occur frequently, we can directly generate the positive and negative balancing prices as following:

Firstly, construct the time series for $\Delta\vartheta^B = \vartheta^+ + \vartheta^- - 2\vartheta^D$. Note that, the positive value of $\Delta\vartheta^B$ indicates the total negative imbalances and the negative value of $\Delta\vartheta^B$ indicates the total positive imbalances, which has been shown in Fig. 3. Secondly, generate scenarios for $\Delta\vartheta^B$. Next, for each scenario of $\Delta\vartheta^B$ we have:

- If $\Delta\vartheta^B > 0$ then $\vartheta^+ = \vartheta^D$; and $\vartheta^- = \Delta\vartheta^B + \vartheta^D$.
- If $\Delta\vartheta^B < 0$ then $\vartheta^- = \vartheta^D$; and $\vartheta^+ = \Delta\vartheta^B + \vartheta^D$.

This mechanism covers the drawback of the imbalance ratios and can be utilized even for the markets which zero prices frequently occur.

- 3: **for** $w = 1$ to total number of wind power production scenarios (N_1) **do**
 - 4: **for** $d = 1$ to total number of DA market price scenarios (N_2) **do**
 - 5: **for** $i = 1$ to total number of ID market price scenarios (N_3) **do**
 - 6: $\vartheta^I(d, i) = \vartheta^D(d) - \Delta\vartheta^I(i)$
 - 7: **for** $b = 1$ to total number of balancing market price scenarios (N_4) **do**
 - 8: **if** $R(b) \geq 1$ **then**
 - 9: $R^+(b)$ and $R^-(b)$ calculated as follows:

$$\begin{cases} R^+(b) = 1; & \text{and } \vartheta^+(d, b) = \vartheta^D(d). \\ R^-(b) = R(b); & \text{and } \vartheta^-(d, b) = \vartheta^D(d) \times R(b). \end{cases}$$
 - 10: **else if** $R(b) < 1$ **then**
 - 11: $R^+(b)$ and $R^-(b)$ calculated as follows:

$$\begin{cases} R^+(b) = R(b); & \text{and } \vartheta^+(d, b) = \vartheta^D(d) \times R(b). \\ R^-(b) = 1; & \text{and } \vartheta^-(d, b) = \vartheta^D(d). \end{cases}$$
 - 12: **end if**
 - 13: $SCN(w, d, i, b) = [W(w); \vartheta^D(d); \vartheta^I(d, i); (R^+(b), R^-(b))]$
 - 14: **end for**
 - 15: **end for**
 - 16: **end for**
 - 17: **end for**
-

more research and is beyond the scope of this paper². Therefore, a symmetric scenario tree can be constructed by generating related scenarios independently, and combining them as follows. Firstly, N_1 scenarios for the DA market price are generated. Next, conditional on each realization of the DA market prices, N_2 possible realization of $(\vartheta^D - \vartheta^I)$ are simulated. Afterwards, simulate N_3 scenarios of the wind power output for every realization of ID market prices. Finally, for each realization of wind power, model N_4 scenarios for imbalance price ratios. Thus, the total number of scenarios is $N_\Omega = N_1 \times N_2 \times N_3 \times N_4$. Algorithm 1 indicates the process of scenario generation for one time period.

IV. MATHEMATICAL FORMULATION

A. Demand Side Offering Model

At first, the stochastic decision model for DS participation in both DA and ID market is developed. Accordingly, the relationship between price and demand is considered to be exponential [26] as in (1).

$$D_t = k \cdot \exp(\sigma \cdot \vartheta_t) \quad (1)$$

where, k is a constant. Notice that σ is a negative number. The profit function of DS, $S(\text{€})$, for the demand D_t can be

²In order to consider the correlation between the wind production and the market prices, a simple way is to consider the market prices as the inputs of neural network for wind power prediction and utilizing a feature selection method to find possible correlation.

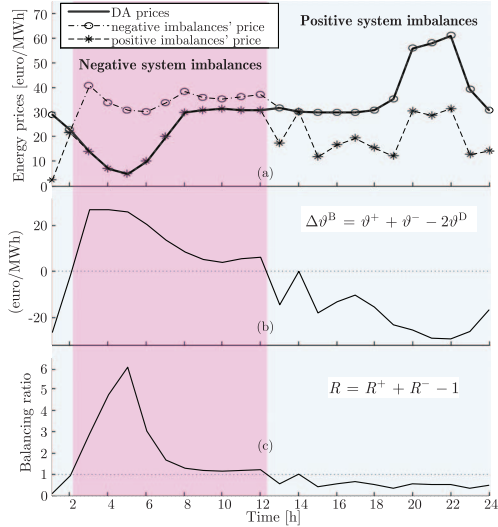


Fig. 3. a) One sample scenario for DA prices and prices of the positive/negative imbalances. b) graphical illustration of the series $\Delta\vartheta^B = \vartheta^+ + \vartheta^- - 2\vartheta^D$ in time horizon of a day. c) graphical illustration of the series $R = R^+ + R^- - 1$ in time horizon of a day.

formulated as their benefits minus costs.

$$S(D_t) = B(D_t) - D_t \cdot \vartheta_t \quad (2)$$

In order to maximize the DS profit, $\frac{\partial S(D_t)}{\partial D_t}$ should be equal to zero, thus,

$$\frac{\partial S(D_t)}{\partial D_t} = \frac{\partial B(D_t)}{\partial D_t} - \vartheta_t = 0 \quad (3)$$

And therefore

$$\frac{\partial B(D_t)}{\partial D_t} = \vartheta_t \quad (4)$$

Regarding to (1) and (4):

$$\left. \frac{\partial^2 B(D_t)}{\partial (D_t)^2} \right|_{D_t=D_0} = \left. \frac{\partial \vartheta_t}{\partial D_t} \right|_{D_t=D_0} = \frac{1}{\sigma \cdot D_{0t}} \quad (5)$$

The Taylor series of DS benefit function around D_0 are as follows.

$$B(D_t) = B(D_{0t}) + (D_t - D_{0t}) \cdot \left. \frac{\partial B(D_t)}{\partial D_t} \right|_{D_t=D_0} + \frac{1}{2} \cdot (D_t - D_{0t})^2 \cdot \left. \frac{\partial^2 B(D_t)}{\partial (D_t)^2} \right|_{D_t=D_0} \quad (6)$$

Therefore, from (4), (5) and (6) we have

$$B(D_t) = B(D_{0t}) + (D_t - D_{0t}) \cdot \vartheta_t + \frac{1}{2} \cdot (D_t - D_{0t})^2 \cdot \frac{1}{\sigma \cdot D_{0t}} \quad (7)$$

Equation (7) is the benefit function that mostly used in the area for an aggregate model [26].

According to the market rules, the DS profit function in response to the load reduction is comprised of several terms.

TABLE I
DIFFERENT SCHEMES FOR INCENTIVE PAYMENT

Periods (time horizon)	Low demand period (1:00-9:00)	Off-peak period (10:00-19:00)	Peak period (20:00-24:00)
fixed incentive rate			
rate	ϑ^*	ϑ^*	ϑ^*
Percentage of DA market prices			
m_t (capacity payment)	100%	100%	100%
m_t (period pricing)	40%	70%	110%

As mentioned in section II-B, this paper considers that DS will be awarded an energy payment and an incentive for their load reduction. In addition, load reduction imposes a cost on consumers which should be considered in their profit function. Thus, DS profit function can be expressed as follows.

$$DS_{\text{profit}} = \overbrace{DS_{\text{ene-pay}} + DS_{\text{incentive}}}^{\text{Revenue}} - DS_{\text{cost}} \quad (8)$$

Where $DS_{\text{ene-pay}}$ is the energy payment which for hour t is as follows

$$DS_{\text{ene-pay}} = (D_{0t} - D_t) \cdot \vartheta_t \quad (9)$$

To model the incentive, three different schemes have been proposed in this context which are shown in Table I.

Policy scheme A: The incentive is paid on a pre-specified fixed rate for each MW load reduction. Equation (10) represent the incentive payment based on the fixed incentive rate scheme.

$$DS_{\text{incentive}} = (D_{0t} - D_t) \cdot \vartheta^* \quad (10)$$

Policy scheme B: In the second scheme, loads will be awarded the capacity payment based on the market prices for their load reduction and can be expressed as (11).

Policy scheme C: Period pricing is another scheme which the incentive is given according to the time horizon and MCP. Because of this, the demand curve is divided into three periods: 1) low demand period, 2) off-peak period and 3) peak period. In the proposed model, the DS revenue is dependent on three periods above and can be expressed as (11).

$$DS_{\text{incentive}} = m_t \cdot (D_{0t} - D_t) \cdot \vartheta_t \quad (11)$$

where, the value of m_t is presented in Table I.

Moreover, DS has a cost for load reduction. The difference between DS profit function before and after load reduction could be considered as DR cost. DRP is assumed to be a price-taker, therefore, regarding to equations (2) and (7), we have

$$S(D_t) = S(D_{0t}) + \frac{1}{2} \cdot (D_t - D_{0t})^2 \cdot \frac{1}{\sigma \cdot D_{0t}} \quad (12)$$

Finally, based on the fixed rate incentive, the profit function of DRP for hour t is achieved by substituting (9), (10) and (12) into (8).

$$DS_{\text{profit}} = (D_{0t} - D_t) \cdot \vartheta_t + (D_{0t} - D_t) \cdot \vartheta^* + \frac{1}{2} \cdot (D_{0t} - D_t)^2 \cdot \frac{1}{\sigma \cdot D_{0t}} \quad (13)$$

Suppose $(D_{0t} - D_t) = L_t$ is the value of DRP offer. Therefore, the DRP profit in time horizon N_T can be written as (14)

$$DS_{\text{profit}} = \sum_{t=1}^{N_T} \left[L_t \cdot \vartheta_t + L_t \cdot \vartheta^* + \frac{1}{2} \cdot \frac{1}{\sigma \cdot D_{0t}} \cdot (L_t)^2 \right] \quad (14)$$

Note that, for those markets which DRP are permitted to purchase energy from the market, a penalty term should be considered which the model is proposed in Appendix.

The DRP offer is limited by the technical constraint as below:

$$0 \leq L_t \leq \eta_1 \cdot D_{0t} \quad \forall t \quad (15)$$

$$\sum_{t=1}^{N_T} L_t \leq \mu \cdot \sum_{t=1}^{N_T} D_{0t} \quad (16)$$

According to the market structure, the formulation is developed as a two-stage stochastic programming for DRP participation in both DA and ID market considering DA and ID market price as the random variables. Accordingly, we have,

$$DS_{\text{profit}} = DS_{\text{revenue}} \Big|_{\text{DA market}} + DS_{\text{revenue}} \Big|_{\text{ID market}} - DS_{\text{cost}} \quad (17)$$

With respect to (14) and (17) we have:

$$\begin{aligned} & \text{Maximize}_{L_t^D \forall t; L_{t\omega}^{\text{sch}}, L_{t\omega}^I \forall t \forall \omega} \{ \varepsilon_{\text{profit}}^{\text{DRP}} \} = \\ & \sum_{t=1}^{N_T} \left[\begin{array}{l} \mathbb{E}_{\Omega_1} \left[\vartheta_{t\omega}^D \cdot L_t^D + \vartheta^* \cdot L_t^D \right] \\ \mathbb{E}_{\Omega_2 | \Omega_1} \left[\begin{array}{l} \vartheta_{t\omega}^I \cdot L_{t\omega}^I + \vartheta^* \cdot L_{t\omega}^I + \\ \frac{1}{2} \cdot \frac{1}{\sigma \cdot D_{0t}} \cdot (L_{t\omega}^{\text{sch}})^2 \end{array} \right] \end{array} \right] \quad (18) \end{aligned}$$

Subject to:

$$L_{t\omega}^{\text{sch}} = L_t^D + L_{t\omega}^I \quad \forall t, \forall \omega \quad (19)$$

$$0 \leq L_t^D \leq \eta_1 D_{0t} \quad \forall t, \forall \omega \quad (20)$$

$$0 \leq L_{t\omega}^{\text{sch}} \leq \eta_1 D_{0t} \quad \forall t, \forall \omega \quad (21)$$

$$\sum_{t=1}^{N_T} L_{t\omega}^{\text{sch}} \leq \mu \cdot \sum_{t=1}^{N_T} D_{0t} \quad \forall \omega \quad (22)$$

where, constraint (19) defines the total scheduled load reduction offer in the both DA and ID markets. Constraint (20) limits DRP's load reduction offer in the DA market. Constraint (21) bounds the total scheduled load reduction offer. Notice that, the flexibility of load (load shifting and interruption range) is modeled through constraints (20)–(22). The lower bound of these constraints are zero, because the DRP are only permitted to bid its load reduction in the same manner that generators offer their production. Firstly, the load shifting/interruption capability of the individual consumers should be declared to DRP through communication/decision tools as shown in Fig. 2. Afterwards, DRP estimates the load shifting and interruption range of the total aggregated load and models them by means of η and μ . DS interruption range is defined by μ . In fact, the minimum percentage of the load which is needed during the day is indicated

by $(1 - \mu) \times 100\%$. This percentage of load must be recovered, even if shifted in the time horizon of a day. Therefore, DRP can offer $\mu \cdot \sum_{t=1}^{N_T} D_{0t}$ in the appropriate period during the time horizon of a day as a generation resource.

It should be mentioned that each term $(\vartheta^* \cdot L_t)$ in (18) should be replaced with $m_t(\vartheta_t \cdot L_t)$ to obtain the model for two other incentive schemes.

B. Wind Power Producer Offering Model

The WPP offering strategy model corresponding to the expected value of daily profit function according to the proposed market framework and considering the market prices (DA, ID and balancing market price) and wind generation as random variables can be expressed as equation (23).

$$\begin{aligned} & \text{Maximize}_{P_{t\omega}^D, P_{t\omega}^I, P_{t\omega}^{\text{sch}}, \delta_{t\omega}^+, \delta_{t\omega}^- \forall t \forall \omega; z_\omega \forall \omega; var} \\ & \{ \varepsilon_{\text{profit}}^{\text{WPP}} \} = \sum_{t=1}^{N_T} \left[\begin{array}{l} \mathbb{E}_{\Omega_1} \left[\vartheta_{t\omega}^D \cdot P_{t\omega}^D + \mathbb{E}_{\Omega_2 | \Omega_1} \left[\vartheta_{t\omega}^I \cdot P_{t\omega}^I \right. \right. \\ \left. \left. + \mathbb{E}_{\Omega_3 | \Omega_2, \Omega_1} \left[\begin{array}{l} \vartheta_{t\omega}^D \cdot R_{t\omega}^+ \cdot \delta_{t\omega}^+ \\ -\vartheta_{t\omega}^D \cdot R_{t\omega}^- \cdot \delta_{t\omega}^- \end{array} \right] \right] \right] \end{array} \right] \\ & + \beta \left(var - (1 - \alpha)^{-1} \sum_{\omega=1}^{N_\Omega} \rho_\omega z_\omega \right) \quad (23) \end{aligned}$$

The objective function (23) to be maximized is comprised of two terms: i) the expected profit of WPP which is equal to its revenue, since its generation cost is assumed to be zero. Revenue from selling energy in DA market plus the revenue/cost from selling/purchasing energy in ID market plus the revenue from the positive energy deviations in the balancing market minus the cost of negative energy deviations in the balancing market constitutes the expected revenue of WPP which is represented within the bracket; and ii) the CVaR multiplied by a weighting factor β , which allows to manage the degree of risk-aversion for WPP.

In (23), the term $(\vartheta_{t\omega}^D \cdot P_{t\omega}^D)$ indicates the revenue from DA market, the term $(\vartheta_{t\omega}^I \cdot P_{t\omega}^I)$ shows the revenue/cost from ID market, the term $(\vartheta_{t\omega}^D \cdot R_{t\omega}^+ \cdot \delta_{t\omega}^+)$ expresses the revenue from the positive energy deviations in the balancing market, and the term $(\vartheta_{t\omega}^D \cdot R_{t\omega}^- \cdot \delta_{t\omega}^-)$ indicates the cost of negative energy deviations in the balancing market in period t and scenario ω . Note that, if the scenarios of the balancing market prices are generated directly, then the term $(\vartheta_{t\omega}^D \cdot R_{t\omega}^+)$ should be replaced by $(\vartheta_{t\omega}^+)$ and the term $(\vartheta_{t\omega}^D \cdot R_{t\omega}^-)$ should be replaced by $(\vartheta_{t\omega}^-)$.

Due to the market rules and technical constraints, short term trading problem of WPP includes the following constraints:

$$0 \leq P_{t\omega}^D \leq W^{\text{max}} \quad \forall t, \forall \omega \quad (24)$$

$$P_{t\omega}^{\text{sch}} = P_{t\omega}^D + P_{t\omega}^I \quad \forall t, \forall \omega \quad (25)$$

$$0 \leq P_{t\omega}^{\text{sch}} \leq W^{\text{max}} \quad \forall t, \forall \omega \quad (26)$$

$$\delta_{t\omega} = W_{t\omega} - P_{t\omega}^{\text{sch}} \quad \forall t, \forall \omega \quad (27)$$

$$\delta_{t\omega} = \delta_{t\omega}^+ - \delta_{t\omega}^- \quad \forall t, \forall \omega \quad (28)$$

$$0 \leq \delta_{t\omega}^+ \leq W_{t\omega} \quad \forall t, \forall \omega \quad (29)$$

$$0 \leq \delta_{t\omega}^- \leq W^{\text{max}} \quad \forall t, \forall \omega \quad (30)$$

$$(P_{t\omega}^D - P_{t\omega'}^D) \cdot (\vartheta_{t\omega}^D - \vartheta_{t\omega'}^D) \geq 0 \quad \forall t, \forall \omega, \forall \omega' \quad (31)$$

$$P_{t\omega}^D = P_{t\omega'}^D \quad \forall t, \forall \omega, \forall \omega' : \vartheta_{t\omega}^D = \vartheta_{t\omega'}^D \quad (32)$$

$$P_{t\omega}^I = P_{t\omega'}^I \quad \forall t, \forall \omega, \forall \omega' : \vartheta_{t\omega}^I = \vartheta_{t\omega'}^I \quad (33)$$

$$\gamma \cdot P_{t\omega}^D \leq P_{t\omega}^I \leq \gamma \cdot P_{t\omega}^D \quad \forall t, \forall \omega \quad (34)$$

$$-\sum_{t=1}^{N_T} \left[\vartheta_{t\omega}^D \cdot P_{t\omega}^D + \vartheta_{t\omega}^I \cdot P_{t\omega}^I + \vartheta_{t\omega}^D (R_{t\omega}^+ \cdot \delta_{t\omega}^+ - R_{t\omega}^- \cdot \delta_{t\omega}^-) \right] + var - z_\omega \leq 0 \quad \forall \omega \quad (35)$$

$$z_\omega \geq 0 \quad \forall \omega \quad (36)$$

Constraint (24) limits the WPPs' offer in the DA market. Constraint (25) represents the total scheduled energy in both DA and ID markets. Constraint (26) bounds the total scheduled energy. Constraint (27) defines the total deviation incurred by WPP. Constraints (29) and (30) state the positive and negative deviations cap, respectively. Constraints (31) and (32) are related to the offering curve which the first one imposes non-decreasing condition and the second one imposes non-anticipative condition for the DA energy offer. Constraint (33) models the non-anticipative condition for the decision made in the ID market. Constraint (34) limits the energy that WPP can sell/purchase in ID market to the certain percentage of the energy sold in the DA market. As mentioned in section II-A, ID markets supposed to be *adjustment market* and it is only for decreasing the imbalances and therefore a generator should not systematically sell energy if it is not capable of producing it at all. Constraints (35) and (36) relate to the calculation of CVaR.

In the stochastic programming model, the risk management is an important issue. CVaR can provide practical large scale calculation, since it can be modeled through linear programming approach. In addition, it can be readily incorporated into the optimization problem [27]. Therefore, it used in this work as a risk measurement.

C. Hybrid Power Plant Offering Strategy Model

By integrating WPP and DR model, the offering strategy for HPP is derived as follows:

$$\xi_{\text{profit}}^{\text{HPP}} = \text{HPP}_{\text{revenue}} - \text{DS}_{\text{cost}} \quad (37)$$

Therefore

$$\begin{aligned} & \text{Maximize} \\ & P_{t\omega}^D, P_{t\omega}^I, P_{t\omega}^{\text{sch,hpp}}, \delta_{t\omega}^{+, \text{hpp}}, \delta_{t\omega}^{-, \text{hpp}}, L_{t\omega}^{\text{sch}} \quad \forall t, \forall \omega; L_t^D \quad \forall t; z_\omega \quad \forall \omega; var \\ & \left\{ \xi_{\text{profit}}^{\text{HPP}} \right\} = \\ & \sum_{t=1}^{N_T} \left[\mathbb{E}_{\Omega_1} \left[\vartheta_{t\omega}^D \cdot P_{t\omega}^D \right] \right. \\ & \quad \left. + \mathbb{E}_{\Omega_2 | \Omega_1} \left[\vartheta_{t\omega}^I \cdot P_{t\omega}^I + \frac{1}{2} \cdot \frac{1}{\sigma \cdot D_{0t}} \cdot (L_{t\omega}^{\text{sch}})^2 \right] \right. \\ & \quad \left. + \mathbb{E}_{\Omega_3 | \Omega_2, \Omega_1} \left[\vartheta_{t\omega}^D \cdot R_{t\omega}^+ \cdot \delta_{t\omega}^{+, \text{hpp}} - \vartheta_{t\omega}^D \cdot R_{t\omega}^- \cdot \delta_{t\omega}^{-, \text{hpp}} \right] \right] \\ & + \beta \left(var - (1 - \alpha)^{-1} \sum_{\omega=1}^{N_\Omega} \rho_\omega z_\omega \right) \quad (38) \end{aligned}$$

Subject to:

$$0 \leq P_{t\omega}^D, \text{hpp} \leq W^{\text{max}} + \eta_1 D_{0t} \quad \forall t, \forall \omega \quad (39)$$

$$P_{t\omega}^{\text{sch,hpp}} = P_{t\omega}^{D,\text{hpp}} + P_{t\omega}^{I,\text{hpp}} \quad \forall t, \forall \omega \quad (40)$$

$$0 \leq P_{t\omega}^{\text{sch,hpp}} \leq W^{\text{max}} + \eta_1 D_{0t} \quad \forall t, \forall \omega \quad (41)$$

$$\delta_{t\omega}^{\text{hpp}} = W_{t\omega} + L_{t\omega} - P_{t\omega}^{\text{sch,hpp}} \quad \forall t, \forall \omega \quad (42)$$

$$\delta_{t\omega}^{\text{hpp}} = \delta_{t\omega}^+ - \delta_{t\omega}^- \quad \forall t, \forall \omega \quad (43)$$

$$0 \leq \delta_{t\omega}^{+, \text{hpp}} \leq W_{t\omega} + L_{t\omega} \quad \forall t, \forall \omega \quad (44)$$

$$0 \leq \delta_{t\omega}^{-, \text{hpp}} \leq W^{\text{max}} + \eta_1 D_{0t} \quad \forall t, \forall \omega \quad (45)$$

$$\left(P_{t\omega}^{D,\text{hpp}} - P_{t\omega'}^{D,\text{hpp}} \right) \cdot \left(\vartheta_{t\omega}^D - \vartheta_{t\omega'}^D \right) \geq 0 \quad \forall t, \forall \omega, \forall \omega' \quad (46)$$

$$P_{t\omega}^{D,\text{hpp}} = P_{t\omega'}^{D,\text{hpp}} \quad \forall t, \forall \omega, \forall \omega' : \vartheta_{t\omega}^D = \vartheta_{t\omega'}^D \quad (47)$$

$$-\gamma \cdot P_{t\omega}^{D,\text{hpp}} \leq P_{t\omega}^{I,\text{hpp}} \leq \gamma \cdot P_{t\omega}^{D,\text{hpp}} \quad \forall t, \forall \omega \quad (48)$$

$$-\sum_{t=1}^{N_T} \left[\vartheta_{t\omega}^D \cdot P_{t\omega}^{D,\text{hpp}} + \vartheta_{t\omega}^I \cdot P_{t\omega}^{I,\text{hpp}} + \frac{1}{2} \cdot \frac{1}{\sigma \cdot D_{0t}} \cdot (L_{t\omega}^{\text{sch}})^2 + \vartheta_{t\omega}^D \cdot R_{t\omega}^+ \cdot \delta_{t\omega}^{+, \text{hpp}} - \vartheta_{t\omega}^D \cdot R_{t\omega}^- \cdot \delta_{t\omega}^{-, \text{hpp}} \right] + var - z_\omega \leq 0 \quad \forall \omega \quad (49)$$

$$z_\omega \geq 0 \quad \forall \omega \quad (50)$$

$$L_{t\omega}^{\text{sch}} = L_t^D + L_{t\omega}^I \quad \forall t, \forall \omega \quad (51)$$

$$\eta_2 D_{0t} \leq L_t^D \leq \eta_1 D_{0t} \quad \forall t, \forall \omega \quad (52)$$

$$\eta_2 D_{0t} \leq L_{t\omega}^{\text{sch}} \leq \eta_1 D_{0t} \quad \forall t, \forall \omega \quad (53)$$

$$\sum_{t=1}^{N_T} L_{t\omega}^{\text{sch}} \leq \mu \cdot \sum_{t=1}^{N_T} D_{0t} \quad \forall \omega \quad (54)$$

$$L_{t\omega}^{\text{sch}} = L_{t\omega'}^{\text{sch}} \quad \forall t, \forall \omega, \forall \omega' : \vartheta_{t\omega}^D = \vartheta_{t\omega'}^D \quad (55)$$

$$L_{t\omega}^I = L_{t\omega'}^I \quad \forall t, \forall \omega, \forall \omega' : \vartheta_{t\omega}^I = \vartheta_{t\omega'}^I \quad (56)$$

Note that, the subscript hpp stands for the hybrid power plant.

Note that, the WPP and DRP constraints are combined through equations (39)–(50). The HPPs' offer in the DA market is limited by constraint (39). In (39), $W^{\text{max}} + \eta_1 D_0$ defines the maximum capacity of the HPP where the first term is related to the wind farm capacity and the second term is related to the DRP. The HPP is considered to be a generation company and therefore, the lower limit of (39) is equal to zero. Constraint (40) indicates the total scheduled power with respect to the DA and ID offers. Constraint (41) limits the scheduled power of HPP. Constraints (42)–(45) characterize the total, negative, and positive imbalances of the HPP based on the wind power production, scheduled power and the values of DR. Constraints (46) and (47) provide the offering curves. Constraint (48) determines the lower and upper bound of the ID offer with respect to the DA offer. Constraints (49) and (50) are required for the risk calculation. Constraints (51)–(56) model the flexible load where (55) and (56) are added to state the non-anticipativity of decision in ID market. The lower limits of constraints (52)–(53) have decreased from zero to $\eta_2 D_{0t}$. This is due to the fact that DS can utilize wind energy and increase their load in JO.

V. CASE STUDY

In order to assess the performance of the proposed strategy, a realistic case study based on a wind farm in Spain has been studied in this section following the rules of the Spanish electricity market.

A. Data

The proposed approach has been implemented on a realistic case study based on the Sotavento wind farm [28] in Spain. The total wind capacity is 17.56 MW. The wind power stochastic process is modeled through the method described in section III-B based on the methodology in [23]. Note that the historical data of year 2010 are the main inputs to train the artificial neural network. The scenarios for market prices are characterized by aforementioned three-step method based on the forecast engine in [24]. The historical data of demand and market prices used in this context belong to the electricity market of Iberian Peninsula as addressed in [29].

The uncertainties appertained to the problem are modeled through a symmetric scenario tree which respectively consists of ten, five, and six scenarios for DA, ID, and balancing market prices in addition to ten scenarios for the wind generation. Therefore, the scenario tree includes 3000 scenarios ($10 \times 5 \times 10 \times 6$).

The simulation result is represented for one week (7 March 2010-13 March 2010). It is assumed that $\frac{1}{1500}$ of the total loads of the Spanish electricity market is aggregated and they participate in the market by means of a DRP.

B. GAMS/MATLAB Interface

In order to implement the proposed model, firstly the process of scenario generation and reduction according to the aforementioned approach is carried out through MATLAB. Afterwards, these data, i.e., inputs of optimization problem, are imported to General Algebraic Modeling System (GAMS) [30] with GAMS/MATLAB Interface [31]. Next, the optimization problem has been solved using GAMS. Finally the output data of GAMS are exported to MATLAB for more analysis. It should be mentioned that all the simulations are carried out on a computer with 6 GB of RAM, and the offering strategy problem has been solved using CPLEX 12 under GAMS on a Windows-based personal computer Intel® CORE™i7 with processors clocking at 2.1 GHz and 6 GB of RAM in less than one minutes.

C. Results and Discussion

The proposed models are capable of producing either “*optimal generation bids*” or “*optimal offering curves*” based on the market rules. The *generation bids* that are submitted to the DA market indicate an *energy quantity* and possibly a *price quantity* which in the case of WPP and HPP are submitted at zero price for assurance that the bids get accepted. Some of the electricity markets allow their participants to submit *offering curves* rather than *generation bids*. The *offering curves* which are submitted to DA market shows a curve which the offered energy quantity can be different for each prices. Both of the cases are discussed below.

1) *Optimal Energy Quantity*: Firstly, the condition terms in constraints (32) and (47) are not included in the optimization problem. In this case, by considering $\beta = 0$ (risk neutral problem), the solution of the optimization models provides the optimal energy quantity for the daily market. Fig. 4 shows the

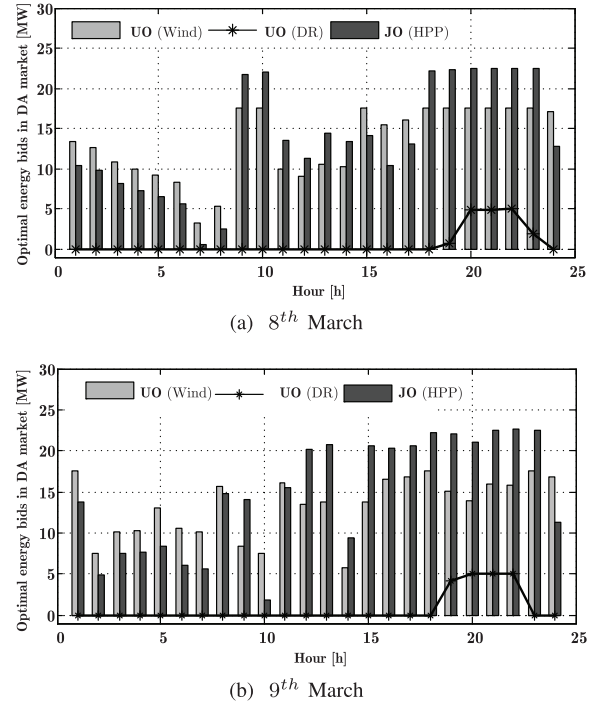


Fig. 4. Optimal offering quantity in the DA market for three different configurations.

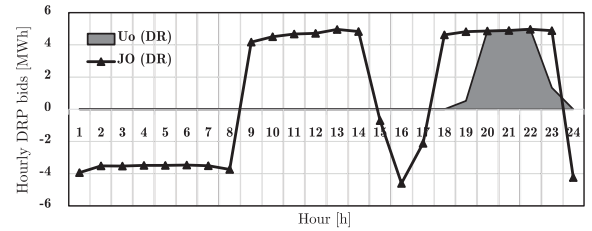


Fig. 5. Hourly DRP bids on March 8, 2010.

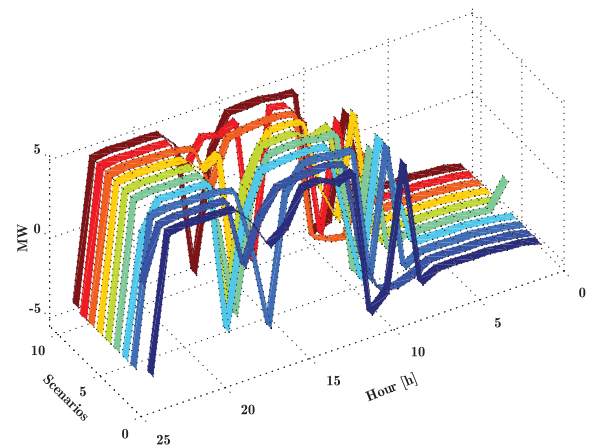


Fig. 6. Scheduled DR in JO for different realization of DA market prices on March 9, 2010.

optimal energy quantity for each time period in two days of the test week obtained for each configuration. As it can be seen from the offering quantity, the joint unit offering quantity increases during peak hours due to the participation of DS. Moreover, JO and UO of WPP and DRP are compared in this

TABLE II
EXPECTED PROFIT IN THE DA MARKET FOR TEST WEEK

Case		07/3/2010	08/3/2010	09/3/2010	10/3/2010	11/3/2010	12/3/2010	12/3/2010	
Expected profit (€)	UO	WPP	3115.1	5091.9	4619.1	2444.9	6283.5	1758.3	1431.6
		DRP	808.5	1062.7	1110.5	1139.4	1349.7	1142.6	857.3
		Sum	3923.6	6154.6	5729.6	3584.3	7633.2	2900.9	2288.9
JO	HPP	4006.3	6323.1	5916.8	3672.2	7908.3	3071.1	2409.1	

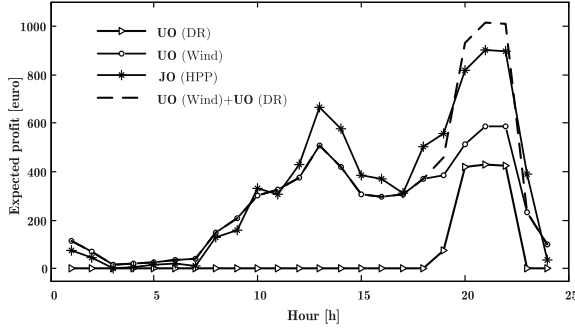


Fig. 7. Hourly expected profit in (€) for three different configuration on March 11, 2010.

figure. Indeed, in JO the optimal quantity is more sensitive to the market prices because of the presence of DR. Note that the DS recovers itself (store more energy) during off-peak hours in JO by using the wind energy. On the other hand, in UO, DRP only offers its load reduction to the daily market in the peak hours. In addition, the correlation between the JO offers and load curve increases 26.61% compared with the independent operation.

Fig. 5 shows the operation of aggregated consumers for one of the scenarios considered (#scenario1). Note that the DRP decreases its load during peak hours and recovers it in off-peak hours by wind energy.

Fig. 6 shows the optimal changes in the behavior of the coordinated DS for each realization of daily market prices.

Table II represents the expected profit of different configurations in the test week. According to the results, HPP's expected profit increases, since DRR mitigate the WPP's uncertainty as well as a more efficient operation, increasing the power sold during the peak hours and increasing the end users' consumption (store more energy) in the off-peak hours. Thus, the operation of the coordinated unit causes an increase for the both wind farm and DRP, since the expected profit of the coordinated farm is more than the sum of the expected profit which is achieved for independent operation. Notice that the expected profit is increased 3.61% during the test week. The models parameters which are used in the case study are $[\alpha, \sigma, \eta_1, \eta_2, \mu, \gamma, \vartheta^*] = [0.95, -0.3, 0.2, -0.2, 0.04, 0.3, 27.68]$. It should be mentioned that the value of ϑ^* is equal to the mean value of DA market prices on February 2010.

The total expected profit for each time period obtained for two configurations in DA market is depicted in Fig. 7. According to the obtained values, in some hours (19:00-22:00) the expected profit in UO is more than JO one. This is due to the fact that DRP receives incentive in UO which is not paid in JO.

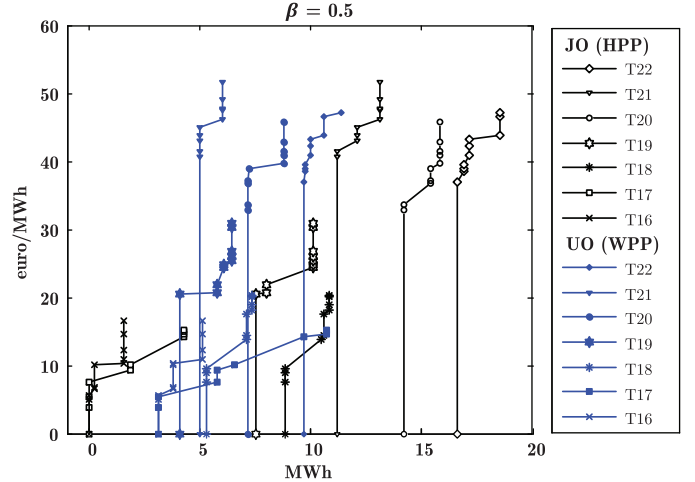


Fig. 8. Optimal Offering Curves on March 10, 2010.

2) *Optimal Offering Curves*: Secondly, the condition term in constraints (32) and (47) is included in the optimization problems. In this case, the solution of the optimization problems includes the optimal *offering curves* rather than only *energy quantity*. The results for hours (16:00-22:00) are shown in Fig. 8. In hours 16:00 and 17:00, the offers of JO are zero for the price lower than 5.46 €/MWh. In this case, all of the wind energy is consumed by demand side. But, if the price of DA market increases, the offered value will raise.

The results, as seen in Fig. 8, indicate that in hours 16:00 and 17:00 the offered values have diminished in JO comparing to the UO. This result can be explained by the fact that the maximum amount of DA market price scenarios for these hours is 16.52 €/MWh and it is lower than the scenarios of prices for other hours. Therefore, due to the low market price in these hours, HPP decreases its bids and the wind energy is consumed by the demand side. On the other hand, in hours 18:00-22:00 the offer curves of JO are higher than one of UO. In this time horizon, the demand side decreases its consumption and therefore, the HPP aggregator can offer more production in the market. Note that, β is considered to be 0.5 in this section. According to the amounts, the JO is more flexible and increases its offer by the increment of the prices more than the uncoordinated one.

3) *Impact of Incorporating Risk into the Problem*: In the previous cases, β is chosen to be 0. To study the impact of risk aversion, the expected profit of WPP and HPP as well as the CVaR are calculated where β increases from 0 to 0.6 with an interval of 0.1. As it can be seen from Table III, if β changes from 0 to 0.6, then CVaR increases 36.3% and the expected value decreases 3.0% for HPP. According to these results, with

TABLE III
COMPARISON OF WPP'S PROFIT AND RISK FOR DIFFERENT VALUES OF β
ON MARCH 9, 2010

β	WPP		HPP	
	Expected profit (€)	CVaR (€)	Expected profit (€)	CVaR (€)
0	5091.9	1866.0	6323.1	3172.5
0.1	5080.9	2068.2	6313.0	3371.1
0.2	4995.8	2658.3	6215.3	4090.5
0.3	4960.0	2806.3	6189.3	4197.5
0.4	4937.8	2871.5	6174.7	4239.3
0.5	4914.4	2924.4	6156.7	4278.6
0.6	4882.2	2983.0	6131.1	4325.2
$-\frac{\Delta(CVaR)}{\Delta(\xi)}$	5.96		6.65	

a low decrease in the expected profit, e.g. 3.0%, the risk of experiencing low profit is diminished very well. Therefore, it can be concluded that CVaR metric can control the risk of the HPP. According to the Table III, for WPP, the CVaR increases 1117€ and the expected profit decreases 4.1%. For JO of WPP and DRP, the results are even better. In this situation, the CVaR increases 1152.7€ and the value of expected profit decreases 3.0% which yields better results with respect to the UO. In other words, for a moderate decrease in the expected profit, a significant increase in CVaR is achieved which is desirable. Also, in the last row of Table III, the ratio $-\frac{\Delta(CVaR)}{\Delta(\xi)}$ is computed. The higher value of the ratio $-\frac{\Delta(CVaR)}{\Delta(\xi)}$ means lower decrease in the expected profit and/or more increase in CVaR. Accordingly, the higher ratio indicates that the risk of the profit variability is controlled better. The result shows that the ratio is higher in the JO with respect to the others. Therefore, it confirms that the JO of WPP and DRP is an effective alternative to diminish the profit variability, risk of experiencing low profit and improve the competitiveness of the WPP in the power market.

In order to assess the effect of risk aversion parameter on the optimal offers of WPP and HPP, we have evaluated the optimal "offering curves" and "generation bids" for the different values of β . Fig. 9 shows the offering curves for two sample hours for different values of β . The results of this study indicate that when the WPP and HPP become more risk averse, by increasing the β value in the models, they intend to reduce the expected energy of their scheduled power (power offered to the DA and ID market) in the hopes that their extra generation can be traded in the balancing market at the still competitive prices. For example, according to the Fig. 9, for $t = 20$, when β is equal to zero (risk neutral problem), the HPP tend to offer the maximum capacity but as it becomes more risk averse ($\beta = 0.4$), the optimal offering curve changes and it prefers to reduce their offers in the hopes that it still can sell its extra production in the balancing market at a competitive prices.

4) *Impact of Different Incentive Schemes:* Finally, the impact of different incentive schemes proposed in section IV-A is assessed by comparing the expected profit which is achieved through each scheme. Table IV shows the expected profit of these schemes. Based on the results, this scheme can only affect the expected profit of DRP since in the JO there is not incentive payment. Indeed, this is one of the benefits of the proposed configuration. As can be seen, the added value is decreased as the incentive payment is increased.

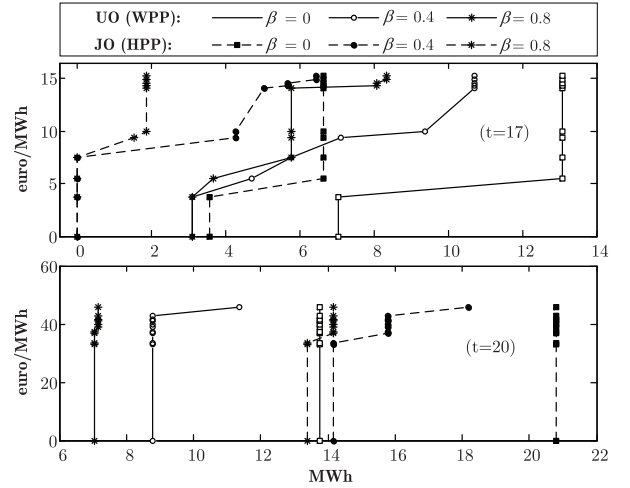


Fig. 9. Optimal offering curves for different values of β in two sample hours on March 10, 2010.

TABLE IV
DIFFERENT INCENTIVE SCHEMES ON MARCH 9, 2010

Incentive schemes		Fixed incentive rate	Capacity payment	Period pricing
Expected profit (€)	UO	WPP	5091.9	5091.9
		DRP	1062.7	1188.7
	JO	HPP	6323.1	6323.1
Added value (€)		168.5	42.5	-17.2

VI. CONCLUSION

This paper proposed a procedure to derive the strategic offer for HPP selling energy in the pool-based market. The problem has been formulated as the three-stage stochastic programming which can be solved using available commercial solver. Numerical results validated the ability of the proposed framework to identify the strategic offer resulting in maximum profit. In addition, it indicated that the JO of WPP and DRP causes an improvement in the expected profit as well as controlling the risk to manage the profit losses comparing to the independent operation. Moreover, the proposed method increased the correlation among the offers and the load curve which this can help to decrease the undispachable nature of the wind power and reduce the variability of the power system with more wind farms. In this paper, it is demonstrated that JO of wind farms and DRR in the short term trading can be achieved by the proposed formulation. In addition to the DA market, DRR accommodated to the ID market which is more effective to cope with the wind power uncertainties.

APPENDIX

In the case of load increase, a penalty term should be considered in the DRP's model. Accordingly, the DRP profit function is comprised of several terms as follows:

$$DS_{\text{Profit}} = DS_{\text{ene-pay}} + \begin{cases} \text{Incentive}_t & : \text{load reduction} \\ \text{Penalty}_t & : \text{load increase} \end{cases} - DS_{\text{cost}} \quad (57)$$

where, $Incentive_t$ and $Penalty_t$ indicate the value of whole incentive/penalty for the load reduction/increase in time period t , respectively. According to the equation (57), in the case of load reduction ($L_t > 0$), the DRPs receive an energy payment plus an incentive for their load reduction minus the cost of reducing their energy. In the case of load increase ($L_t < 0$), the DRPs should pay the price of extra energy in addition to the penalty for their load increase and also the cost resulted from increasing their energy. Note that, the cost term is negative in both situations (load reduction and increase).

Therefore, problem (57) in time horizon N_T can be stated as follows:

$$DS_{\text{Profit}} = \sum_{t=1}^{N_T} \left[L_t \cdot \vartheta_t + \begin{cases} L_t \cdot inc_t & : \text{if } L_t \geq 0 \\ L_t \cdot pen_t & : \text{if } L_t < 0 \end{cases} + \frac{1}{2} \cdot \frac{1}{\sigma \cdot D_{0t}} \cdot (L_t)^2 \right] \quad (58)$$

where, inc_t and pen_t indicate the value of incentive/penalty for each MW load reduction/increase in time period t . These parameters are determined according to the ISO criteria.

The second term of problem (58) is a piecewise function. Therefore, it cannot be solved through optimization techniques. A simple approach to surmount this obstacle is to define a binary variable B_t , per period, indicating the direction, load reduction or increase, of the DRP bid. Therefore, the problem (58) can be recast as:

$$DS_{\text{Profit}} = \sum_{t=1}^{N_T} \left[L_t \cdot \vartheta_t + L_t \cdot inc_t \cdot B_t + L_t \cdot pen_t \cdot (1 - B_t) + \frac{1}{2} \cdot \frac{1}{\sigma \cdot D_{0t}} \cdot (L_t)^2 \right] \quad (59)$$

subject to

$$L_t \leq M \cdot B_t \quad (60)$$

$$-L_t \leq M \cdot (1 - B_t) \quad (61)$$

Note that, B_t is equal to 1 for the load reduction and 0 otherwise.

The second and third terms in problem (59) are both integer, due to the utilization of binary variables B_t , and non-linear, because of the product of variables $L_t \cdot B_t$ and $L_t \cdot (1 - B_t)$. Solving mixed-integer non-linear programming problem is, in general, complex due to the lack of theoretical results guaranteeing its existence and uniqueness. Fortunately, the second and third terms in problem (59) can be simply transformed into a mixed-integer linear one.

The $Incentive_t$ is the product of a limited continuous variable, L_t , a binary variable B_t , and also a parameter inc_t , therefore it can be stated as the following linear inequalities.

$$0 \leq Incentive_t \leq M \cdot B_t \quad (62)$$

$$L_t \cdot inc_t - M(1 - B_t) \leq Incentive_t \leq L_t \cdot inc_t + M(1 - B_t) \quad (63)$$

and also the $penalty_t$ term can be expressed as follows:

$$-M \cdot (1 - B_t) \leq Penalty_t \leq 0 \quad (64)$$

$$L_t \cdot pen_t - MB_t \leq Penalty_t \leq L_t \cdot pen_t + MB_t \quad (65)$$

where, M is a large positive number exceeding any maximum feasible value of $|L_t|$, $|L_t \cdot pen_t|$ and $|L_t \cdot inc_t|$.

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