Strategic Offering for a Price-Maker Wind Power Producer in Oligopoly Markets considering Demand Response Exchange

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***Abstract*—This paper proposes an offering strategy for a Wind Power Producer (WPP) that participates in both day-ahead and balancing oligopoly markets as a price-maker. Penetration of demand response resources into smart grids is modeled by Intraday Demand Response eXchange (IDRX) architecture. A bi-level optimization framework is proposed based on multi-agent system and incomplete information game theory. Modeling the WPPs in high penetration of wind power as price-makers can reflect the capability of this market player to directly affect the market prices. Simulation results indicate that the price-taker model of WPP is not accurate for WPPs that have significant market shares. By comparing the results obtained from modeling the WPPs as price-makers with the ones as price-takers can be concluded that WPPs have the market power not only to increase the prices of both day-ahead and balancing markets, but also to reduce the amount of demand response through IDRX market mechanism.**

***Keywords*—Wind power producer, Demand response exchange, Price-maker, Oligopoly market, Smart grid.**

I. Nomenclature

Abbreviations

CVaR	Conditional Value-at-Risk
DA	Day-Ahead
DR	Demand Response
DRP	Demand Response Provider
DRR	Demand Response Resource
DRX	Demand Response eXchange
Genco	Generation Company
IDRX	Intraday Demand Response eXchange
ISO	Independent System Operator
LMP	Locational Marginal Price
MPEC	Mathematical Program with Equilibrium Constraints
MILP	Mixed Integer Linear Programming
OPF	Optimal Power Flow
REFIT	Renewable Energy Feed-In Tariff
RWM	Roulette Wheel Mechanism
SCED	Security Constrained Economic Dispatch
SCUC	Security Constrained Unit Commitment
SFE	Supply Function Equilibrium
VaR	Value-at-Risk
WPP	Wind Power Producer

Indices

d	index of DRPs
i	index of Gencos
j	index of retailers
k	Index of thermal unit cost segments
ω	index of scenarios

Parameters

$c_{d,t}^{k}$	offered cost of block k of DRP d
$C^{M/O}$	maintenance/operation cost
C^{invest}	investment cost
$D_{j,t}$	demand of retailer j
MU_i, MD_i	minimum up and down times
NK	number of segments of thermal unit cost
r_t^+, r_t^-	positive and negative imbalance ratios
$W_{t,\omega}$	wind power production
$SR_{t,\omega}$	required spinning reserve
α	confidence level
β	weighting factor of taking risk
$\lambda_{i,\omega}^{up}, \lambda_{i,\omega}^{down}$	start-up and shut-down costs
π_{ω}	occurrence probability of scenario ω
RU_i, RD_i	ramp up and down

Variables

$a_{i,\omega}, b_{i,\omega}, c_{i,\omega}$	coefficients of Genco's cost function
B_{ω}	typical profit
$CDRP_{d,t,\omega}$	cost of DR related to DRP d
$D_{j,t,\omega}^{DA}, D_{j,t,\omega}^{Bal}$	day ahead and balancing bids of retailer j
$D_{j,t,\omega}$	total demand of retailer j
$DR_{d,t,\omega}$	amount of power of DRP d traded in IDRX
$e_{j,\omega}, f_{j,\omega}$	coefficients of retailers' income
$F_{t,k,\omega}, F_{t,k,\omega}^{cg}$	branch flow in normal and contingency states
$I_{i,t,\omega}$	commitment state of unit i
$IC_{i,k,\omega}$	incremental cost of unit i at segment k due to linearize the Genco's cost function

The work of M. Shafie-khah and J. P. S. Catalão was supported by FEDER funds through COMPETE and by Portuguese funds through FCT, under FCOMP-01-0124-FEDER-020282 (Ref. PTDC/EEA-EEL/118519/2010) and UID/CEC/50021/2013, and also by the EU 7th Framework Programme FP7/2007-2013 under grant agreement no. 309048 (project SiNGULAR).

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2015.2472339, IEEE Transactions on Industrial Informatics

$P_{t,\omega}^{DA}, P_{t,\omega}^{Bal}$	day ahead and balancing WPP offers
$P_{i,t,\omega}^{DA}, P_{i,t,\omega}^{Bal}$	day ahead and balancing generations of Genco i
$P_{i,t,\omega}^{Res}$	offer of Genco i to day ahead reserve market
$P_{i,t,\omega}$	total generation of Genco i
$P_{t,\omega}^{Sch}$	total scheduled power of WPP
$q_{d,t,\omega}^{k}$	scheduled power of block k of DRP d
$y_{i,t,\omega}, z_{i,t,\omega}$	start-up and shut down binary variables
$\alpha^{SFE}, \beta^{SFE}$	variables of offering strategy
$\Delta_{t,\omega}$	total deviation for wind production
$\Delta_{t,\omega}^{+}, \Delta_{t,\omega}^{-}$	positive and negative deviations
$\lambda_{t,\omega}^{DA}, \lambda_{t,\omega}^{Bal}, \lambda_{t,\omega}^{Res}$	day ahead, balancing and reserve market prices
ξ	value-at-risk
η_{ω}	variable for computing CVaR

II. Introduction

FOLLOWING ambitious targets set by many countries and regions around the world, wind power capacity has entered in a new large-scale development era so that this is not considered as a marginal generation technology anymore. Under this perspective, the previous support schemes that have been implemented for promotion of wind power seem to be inefficient due to the fact that these schemes keep WPPs aside from electricity market mechanisms and make WPPs isolated generation companies. In addition, exposing WPPs into electricity market environment can bring significant additional benefits for power grids such as improving the combination with other technologies, incorporating portfolio effects and procuring transparency concerning the total cost of promotion policy. [1]. As a result of both large-scale developments in wind power capacity and entrance of wind power generation companies to electricity market, WPPs may constitute a major share of the market in some areas. Such dominant positions may result in that some WPPs strategically offer in the market with the aim of increasing their own profits through intentionally altered market clearing prices.

Several methods have been reported in the literature to simulate oligopoly electricity markets. In [2], an equilibrium-band methodology based on the Nash equilibrium has been employed to analyze the electricity markets. In [3], an evolutionary game theoretic model based on genetic algorithm has been reported to simulate the electricity market. In [4], a stochastic game theoretic model based on reinforcement learning has been reported to study power system. In [5], a solution method based on the payoff matrix approach and polynomial equations has been reported to calculate all the market equilibria of multiplayer games in the electricity markets. In [6], a model based on game theory with Nash equilibrium as the solution concept has been presented to simulate the oligopoly behavior of competitors. In order to simplify the solution process has been simplified by using discretized strategies to form matrix games. According to advantages of agent-based methods to model the complex behavior of market players in large-scale systems, in [7], an agent-based method was employed to simulate the market. Moreover, in [8], the electricity market has been simulated by utilizing an agent-based computational economics. Despite the reported methods to simulate the oligopoly electricity markets, modeling the markets from WPP's point of view has been rarely addressed.

Hence, this paper proposes an offering strategy for a WPP with market power that competes with other GenCos and participates in both DA and balancing markets as a price-maker.

On this basis, a stochastic decision making model is presented for the participation of WPP in DA and balancing oligopoly markets. In order to simulate the mentioned oligopoly markets from WPP's point of view, a bi-level optimization model is proposed based on multi-agent system and dynamic game theory. The proposed method considers the SFE to model the offering strategy of all players, which is one of the most accurate models for the simulation of game theory.

In this model, it is supposed that information of market competitors (e.g., cost function of generation units) is not available for the WPP, similarly to reality (incomplete information game theory [9]).

Furthermore, since transmission constraints may create opportunities for the market players to induce congestion to create an uncompetitive market, considering the network and security constraints in market simulation is vital [10]. For this purpose, an SCUC method is used in this paper, including AC power flow limits.

Similar to other market participants, a WPP is obligated to offer its generation to the market one day in advance. Although recent advances in wind power forecast tools are remarkable, DA forecast errors are still significant, which may impose imbalance costs to WPPs.

The utilization of DR [11]-[12], storage devices alongside wind farms [13], and joint operation of wind farms and hydro plants [14] have been suggested to minimize those imbalance costs. However, Ref. [15] indicates that the option with highest flexibility and lowest cost corresponds to DRRs, being nowadays at the core of innovative smart grid technologies.

Moreover, shrinking the periods of wind power forecast from DA to intraday can drastically decrease the forecast errors and it has been proposed to overcome wind power uncertainties [16], [17]. Indeed, formation of such liquid markets close to delivery guarantees that the mentioned flexibility is accessible to those who really need it. At present, strict market rules prevent large potential of DRRs for engaging in the intraday market. In addition, only DA market provides a sufficient incentive for DR participants.

On this basis, this paper applies both the above mentioned solutions developing a novel framework that allows DRRs to contribute into intraday markets. The current paper provides an IDRX market architecture for trading DR between DRPs and DR users (e.g., WPPs).

The most important motivations for the establishment of an intraday DRX market are summarized as follows:

- Demand response resources are mainly small size virtual resources that are not allowed to enter the conventional market due to restrict market regulations. In addition, as demonstrated in[16], market performance under DRX market is considerably better than conventional approaches.

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- Allowing any player to benefit from DR paid by other players causes a suboptimal performance of the market and, consequently, there is a need for a new DR scheduling scheme that fairly allocates DR payments across all players based on the benefit that each player gets from DR and with the aim of ensuring optimum market efficiency [18]. In this situation, DRX structure creates an efficient market for trading DR.

In such architecture, the WPP has to compete with retailers and distributors who purchase DR to improve their profitability and business. The provided architecture can also create an appropriate opportunity for small consumers to deal with multiple DR-involved players in a competitive way. In other word, IDRX market can attract the small consumers by making a competitive environment and consequently it can motivate them to participate in DR programs more actively.

Although offering strategies in both DA and intraday markets have been reported in [19], the mentioned reference has considered the role of WPPs in electricity markets as price-takers. In [20], a stochastic model for wind power production has been reported in order to find the optimal contract sizing by participating in DA and balancing markets. In this reference the impact of market prices on the auxiliary generation and cost of reserves to accommodate the uncertainty of WPP has been analyzed. Moreover, a completely competitive electricity market has been presented; hence all the market players including the WPP have been modeled as price-takers. Even though in some recent papers such as [21]-[23] price-maker WPPs have been studied, the WPP's competitors have been considered entirely competitive. Moreover, in these reports the uncertainty of market players' behavior has not been considered. In [21], a stochastic bi-level MPEC optimization has been used to maximize the WPP's revenue as the objective function. In [22], the WPP's profit has been maximized as the objective function by using a stochastic bi-level MPEC optimization. In [23], a deterministic MILP optimization has been employed to maximize the WPP's profit as the objective function. Additionally, in all previous references the participation of WPPs in DRX markets has not been addressed. The effect of DRX on the offering strategy of WPPs in a completely competitive environment has been investigated in [24] by using a stochastic MILP optimization; however, price-making WPPs and effect of oligopoly environment on the behavior of market players have not been investigated. Since the aim of WPPs is to maximize the profit considering the entire operation cycle, this paper presents three stage trading floors: oligopoly DA, IDRX market, and balancing market. The paper takes into account wind power uncertainties as well as the uncertainties related to market players' behavior and the prices of IDRX market. Moreover, in order to represent the risk preferences of the WPP, a risk management strategy is incorporated to the WPP's objective function using CVaR.

According to the above explanations, the contributions of this paper can be summarized as follows:

- Modeling the oligopoly electricity markets from WPP's point of view considering the network and security constraints.
- Modeling a price-maker WPP in both DA and balancing markets, as well as participating in the IDRX market.
- Modeling the uncertainty of market competitors by using incomplete information dynamic game theory

The paper continues as follows: The formulation of the proposed strategic offering of WPPs is presented in Section II. Section III presents the oligopoly market model. Section IV describes the uncertainty characteristics and the bi-level stochastic programming. Section V is designated to the numerical studies and Section VI concludes the paper.

III. Formulation of the Strategic Offering of Wind Power Producers

A. DR modeling

According to the benefits of DR programs to acquire reliable and efficient power markets, several programs have been legalized and implemented in numerous countries [25]. On this basis, numerous types of electricity demand function have been reported to demonstrate consumers' response (e.g., [26]-[28]). To develop a market-based DR, a player called DRP - who aggregates the customers' responses to participate in the electricity market on behalf of them - is considered. The considered pool-based DRX market belongs to the intraday horizon. This IDRX market architecture not only has additional advantages for WPPs, but also provides greater opportunities for DRPs. The WPP can compensate its unexpected shortages in wind generation by participating in the local IDRX to decrease its imbalance penalties in the balancing market. Moreover, DR participants are incurred to less financial losses because of penalty payment prevention, due to the more accurate DR estimation in a closer time frame to real time operation, and are more and more encouraged to participate in DR programs. A description of the DRPs price-quantity is formulated in (1)-(4). Note that NQ_d represents the number of bidding blocks of DRPs.

$$DR_{d,t,\omega} = \sum_{k=1}^{NQ_d} q_{d,t,\omega}^{k} \tag{1}$$

$$CDRP_{d,t,\omega} = \sum_{k=1}^{NQ_d} c_{d,t}^{k} . q_{d,t,\omega}^{k} \tag{2}$$

$$q_{d,t,\omega}^{k} \leq q_{d,t}^{k,\max} \tag{3}$$

$$DR_{d,t,\omega} \leq DR_{d,t}^{\max} \tag{4}$$

B. Incorporating risk management

The risk measure used in this study in order to demonstrate the integrated risk management problem of a WPP is the conditional value at risk at the confidence level (α-CVaR). This is due to the fact that this metric can be expressed linearly within an optimization problem and exhibits good mathematical properties [29]. By maximizing a discrete profit distribution, α-CVaR can be approximately defined as the expected profit of the (1-α) 100% scenarios with lowest profit, so it can be represented mathematically in (5).

$$CVaR = E\left(B \middle| B \leq \xi\right) \tag{5}$$

The formulation of CVaR is given in the following as it can be seen in (6)-(8) [30]:

$$Max \quad \left\{ \xi - \frac{1}{1-\alpha} \sum_{\omega=1}^{\Omega_N} \pi_{\omega} . \eta_{\omega} \right\} \tag{6}$$

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$$-B_{\omega}+\xi-\eta_{\omega}\leq 0 \tag{7}$$

$$\eta_{\omega}\geq 0 \tag{8}$$

The value of η_{ω} sets to 0 if the profit of scenario ω is higher than ξ. For the remaining scenarios, η_{ω} is assigned to the difference between ξ and the related profit. The amount of α is assigned to 0.95. The constraints (7) and (8) are utilized to unify the risk-metrics CVaR.

C. Objective function

The objective function of a WPP is to maximize the expected profit that can be expressed as:

$$\begin{aligned}&\text{Max}\{\ WPP\text{'}s\ Expected\ Profit\ \}=\\&\sum_{\omega=1}^{\Omega_N}\pi_{\omega}\sum_{t=1}^{T}\left[\begin{array}{l}\lambda_{t,\omega}^{DA}.P_{t,\omega}^{DA}+\lambda_{t,\omega}^{Bal}.P_{t,\omega}^{Bal}\\+\lambda_{t,\omega}^{DA}.r_t^{+}.\Delta_{t,\omega}^{+}-\lambda_{t,\omega}^{DA}.r_t^{-}.\Delta_{t,\omega}^{-}-\sum_{d=1}^{ND}CDRP_{d,t,\omega}\\-C^{M/O}(P_{t,\omega}^{DA}+P_{t,\omega}^{Bal})-C^{invest}\end{array}\right]\\&+\beta\left(\xi-\frac{1}{1-\alpha}\sum_{\omega=1}^{\Omega_N}\pi_{\omega}.\eta_{\omega}\right)\end{aligned} \tag{9}$$

The two first terms in (9) represent the WPP incomes achieved from trading energy to the DA and balancing markets.

The next two terms are related to the incomes and costs in balancing market caused by positive and negative imbalances, respectively. A rational mechanism is considered for imbalances so that producers must resell the excess of generation cheaper than the DA market's price and compensate the short on generation more expensive than DA market's price, same as the implemented mechanism in the electricity market of the Iberian Peninsula [31]. The cost of purchasing DR from IDRX market is represented in the fifth term. The sixth term represents maintenance/operation cost and the next term denotes WPP's investment cost obtained for each hour. Finally, the last term of the objective function is related to risk modeling using CVaR.

In fact, Eq. (6) is related to mathematical representation of CVaR, while, the risk is incorporated into the main objective function in the last term of (9). In other words, the main objective function of the paper includes the expected profit and the CVaR multiplied by the weighting factor β. The factor β models the tradeoff between the expected profit and the CVaR.

It should be noted that β=0 denotes a risk-taker WPP and β=1 represents a risk-averse one. The other considered constraints of the problem are expressed below:

$$0\leq P_{t,\omega}^{DA}\leq P^{\max} \tag{10}$$

$$P_{t,\omega}^{Sch}=P_{t,\omega}^{DA}+P_{t,\omega}^{Bal}-\sum_{d=1}^{ND}DR_{d,t,\omega} \tag{11}$$

$$0\leq P_{t,\omega}^{Sch}\leq P^{\max} \tag{12}$$

$$\Delta_{t,\omega}=W_{t,\omega}-P_{t,\omega}^{Sch} \tag{13}$$

$$\Delta_{t,\omega}=\Delta_{t,\omega}^{+}-\Delta_{t,\omega}^{-} \tag{14}$$

Constraint (10) imposes that offers in DA market should not be higher than the generation capacity of units installed in the wind farm, P^{max}.

The total scheduled energy of WPP in all DA, intraday and balancing markets is shown in (11). Eq. (12) limits the total scheduled energy in each scenario.

Eqs. (13) and (14) are utilized to calculate the total energy deviation using the last scheduled energy (i.e., the sum of the transactions in the DA and intraday markets).

On this basis, when wind generation is higher than the forecasted value in the second stage, the system requires downward regulation services that are provided by other generation units. In such situation, WPPs must sell the excess of their generations at a price lower than DA market's one. On the contrary, in case of wind power shortage, the system requires upward regulation services to compensate the deficit of generation. In this situation, WPPs must cover the shortages at a price higher than DA market's one.

By applying the objective function to (7), the formulation of incorporating risk can be obtained as (15).

$$-\sum_{t=1}^{T}\left[\begin{array}{l}\lambda_{t,\omega}^{DA}.P_{t,\omega}^{DA}+\lambda_{t,\omega}^{Bal}.P_{t,\omega}^{Bal}\\+\lambda_{t,\omega}^{DA}.r_t^{+}.\Delta_{t,\omega}^{+}-\lambda_{t,\omega}^{DA}.r_t^{-}.\Delta_{t,\omega}^{-}\\-\sum_{d=1}^{ND}CDRP_{d,t,\omega}\\-C^{M/O}(P_{t,\omega}^{DA}+P_{t,\omega}^{Bal})-C^{invest}\end{array}\right]+\xi-\eta_{\omega}\leq 0 \tag{15}$$

The strategic behavior of WPP is illustrated in Fig. 1.

IV. Modeling the Oligopoly Market from Wind Power Producer's Viewpoint

In this paper, aiming to improve the reality of the studies, the electricity market has been modeled as an oligopoly market instead of being perfectly competitive. For this purpose, a multi-agent environment based on bi-level optimization has been developed. The agents do not have information of their competitors. Hence, the mentioned environment for the WPP becomes an incomplete information game theory.

It is noteworthy that the expressed method in Section V has been developed to overcome the uncertainties of incomplete information game theory.

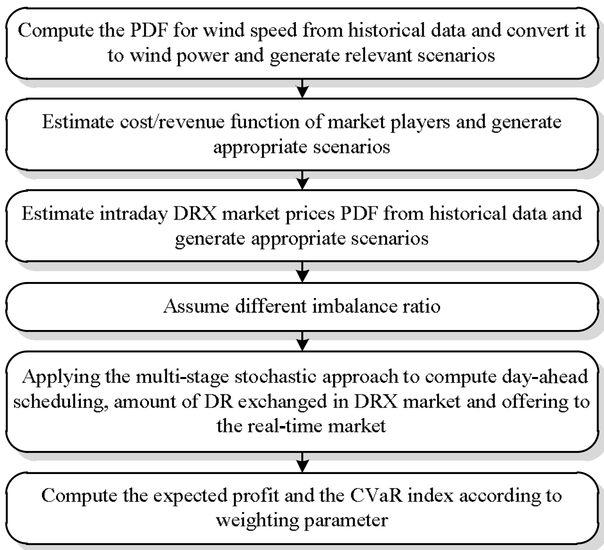

Fig. 1. The proposed framework for strategic behavior of WPP.

The details of the proposed electricity market model from WPP's viewpoint are expressed hereafter.

A. Market players

In the proposed agent-based model, each market player (e.g., Gencos and Retailers) is independently modeled using agents, so that their objective functions correspond to maximize their profit. The objective function of each Genco agent can be formulated as follows:

$$\text{Max}\{Thermal\ Unit's\ Expected\ Profit\} =$$

$$\sum_{\omega=1}^{\Omega_N}\pi_{t,\omega}\sum_{t=1}^{T}\left\{\begin{array}{l} P_{i,t,\omega}^{DA}.\lambda_{t,\omega}^{DA}+P_{i,t.\omega}^{Bal}.\lambda_{t,\omega}^{Bal}+P_{i,t,\omega}^{Res}.\lambda_{t,\omega}^{Res} \\ -\left(\sum_{k=1}^{NK}IC_{i,k,\omega}.P_{i,k,t,\omega}+c_{i,\omega}.I_{i,t,\omega}\right) \\ -\lambda_{i,\omega}^{up}.y_{i,t,\omega}-\lambda_{i,\omega}^{down}.z_{i,t,\omega} \end{array}\right\} \tag{16}$$

subject to:

$$P_i^{\min}.I_{i,t,\omega}\le P_{i,t,\omega}\le P_i^{\max}.I_{i,t,\omega} \tag{17}$$

$$I_{i,t,\omega}-I_{i,t-1,\omega}=y_{i,t,\omega}-z_{i,t,\omega} \tag{18}$$

$$y_{i,t,\omega}+z_{i,t,\omega}\le 1 \tag{19}$$

$$y_{i,t,\omega}+\sum_{j=1}^{MU_i-1}z_{i,t+j,\omega}\le 1 \tag{20}$$

$$z_{i,t,\omega}+\sum_{j=1}^{MD_i-1}y_{i,t+j,\omega}\le 1 \tag{21}$$

$$I_{i,t,\omega}.I_{i,t-1,\omega}.(P_{i,t,\omega}-P_{i,t-1,\omega})\le RU_i \tag{22}$$

$$I_{i,t,\omega}.I_{i,t-1,\omega}.(P_{i,t-1,\omega}-P_{i,t,\omega})\le RD_i \tag{23}$$

where $P_{i,t,\omega}=P_{i,\min}.I_{i,t,\omega}+\sum_{k=1}^{NK}P_{i,k,t,\omega}$ and $P_{i,t,\omega}^{DA}+P_{i,t,\omega}^{Bal}=P_{i,t,\omega}$. Eq. (17) denotes the unit output limits. Constraints of minimum up and down times are linearly expressed in (18)-(21). Constraints of unit ramp up and ramp down are presented in (22) and (23), respectively.

The other considered market players are retailers, so that their objective function can be formulated as follows:

$$\text{Max}\{\ Retailer's\ Expected\ Profit\} =$$

$$\sum_{\omega=1}^{\Omega_N}\pi_{t,\omega}\sum_{t=1}^{T}\left\{-D_{j,t,\omega}^{DA}.\lambda_{t,\omega}^{DA}-D_{j,t,\omega}^{Bal}.\lambda_{t,\omega}^{Bal}+e_{j,\omega}+f_{j,\omega}.D_{j,t}\right\} \tag{24}$$

where $D_{j,t,\omega}^{DA}+D_{j,t,\omega}^{Bal}=D_{j,t}$. All agents utilize the prices of electricity markets obtained from simulating the previous iteration of clearing the market transactions. After that, each agent maximizes its profit by using the mentioned prices to obtain the optimal amount of bid/offer in each hour of next iteration. Afterwards, the agents generate their bidding/offering strategies by applying the optimal quantity and price using SFE model. Among different models reported for offering strategy of market players, only SFE enables a firm to link its offering price with the offering quantity of its product. Therefore, each player uses the SFE vector (α^{SFE}, β^{SFE}) to submit its offers/bids to the markets. α^{SFE} and β^{SFE} are the variables of offering strategy in the supply function equilibrium that represent the slope of price-quantity curve and the y-intercept of price-quantity curve, respectively.

B. Clearing the electricity market transactions

Since the WPPs are limited energy players, their behavior should be modeled in a specific period.

Hence, in this paper, instead of OPF, the role of ISO in DA horizon in clearing the electricity market and determining auction winners has been defined using an SCUC problem [32], which maximizes social welfare considering security constraints. The SCUC problem maximizes the offer-based social welfare as expressed in (25). In addition, the objective of ISO in balancing market is accomplished by an SCED problem as presented in (26).

From ISO's point of view, other constraints should be considered as given below:

$$\text{Max}\{Social\ Welfare\ in\ Day\text{-}ahead\ Market\} =$$

$$\left\{\sum_{t=1}^{T}\left(\sum_{j\in Retailers}D_{j,t,\omega}^{DA}.\lambda_{t,\omega}^{DA}-\sum_{i\in Gencos}\left(P_{i,t,\omega}^{DA}.\lambda_{t,\omega}^{DA}+P_{i,t,\omega}^{Res}.\lambda_{t,\omega}^{Res}\right)\right)\right\} \tag{25}$$

$$\text{Max}\{Social\ Welfare\ in\ Balancing\ Market\} =$$

$$\left\{\sum_{t=1}^{T}\left(\sum_{j\in Retailers}D_{j,t,\omega}^{Bal}.\lambda_{t,\omega}^{Bal}-\sum_{i\in Gencos}P_{i,t,\omega}^{Bal}.\lambda_{t,\omega}^{Bal}\right)\right\} \tag{26}$$

$$\sum_{j\in Retailers}D_{j,t,\omega}^{DA}=\sum_{i\in Gencos}P_{i,t,\omega}^{DA} \tag{27}$$

$$\sum_{j\in Retailers}D_{j,t,\omega}^{Bal}=\sum_{i\in Gencos}P_{i,t,\omega}^{Bal} \tag{28}$$

$$\sum_{i\in Gencos}P_{i,t}^{\max}.I_{i,t,\omega}=\sum_{j\in Retailers}D_{j,t}+SR_{t,\omega} \tag{29}$$

$$-F_k^{\max}\le F_{t,k,\omega}\le F_k^{\max} \tag{30}$$

$$-F_k^{\max}\le F_{t,k,\omega}^{cg}\le F_k^{\max} \tag{31}$$

Eqs. (27) and (28) ensure the balance between supply and demand. The required spinning reserve is expressed in (29). Inequalities (30) and (31) consider the network limits in normal and contingency states, respectively.

C. Relationship between model elements

Fig. 2 shows the proposed WPP's model to simulate the oligopoly behavior of the electricity market. This model can be described as following steps:

- In the first step, each agent self-schedules the operation of its resources to maximize its profit based on the prices of the day-ahead (energy and reserve), the intraday DRX and the balancing markets obtained from the previous iteration. In this step, the WPP considers the uncertainties of the estimated coefficients of players' cost/revenue functions using the method that is provided in Section V in order to reduce the risk of estimating mistakes. The output of this step is the agents' offers/bids (α^{SFE}, β^{SFE}) to participate in both the day-ahead and balancing markets.
- In the second step, the agents' offers/bids are inputted to the SCUC program. Then, the agent of ISO obtains the economic solution to the participant agents in the day-ahead market, considering the security constraints of the system. It should be noted that, in this step, ISO does not consider the agents' offers/bids for the balancing market; therefore, it only aims to maximize the social welfare in the day-ahead market. The output of the step is prices of the day-ahead market and auction winners in the day-ahead energy and reserve markets. The output results from (25) and includes the mentioned prices and auctions for all 24 hours of the day ahead.

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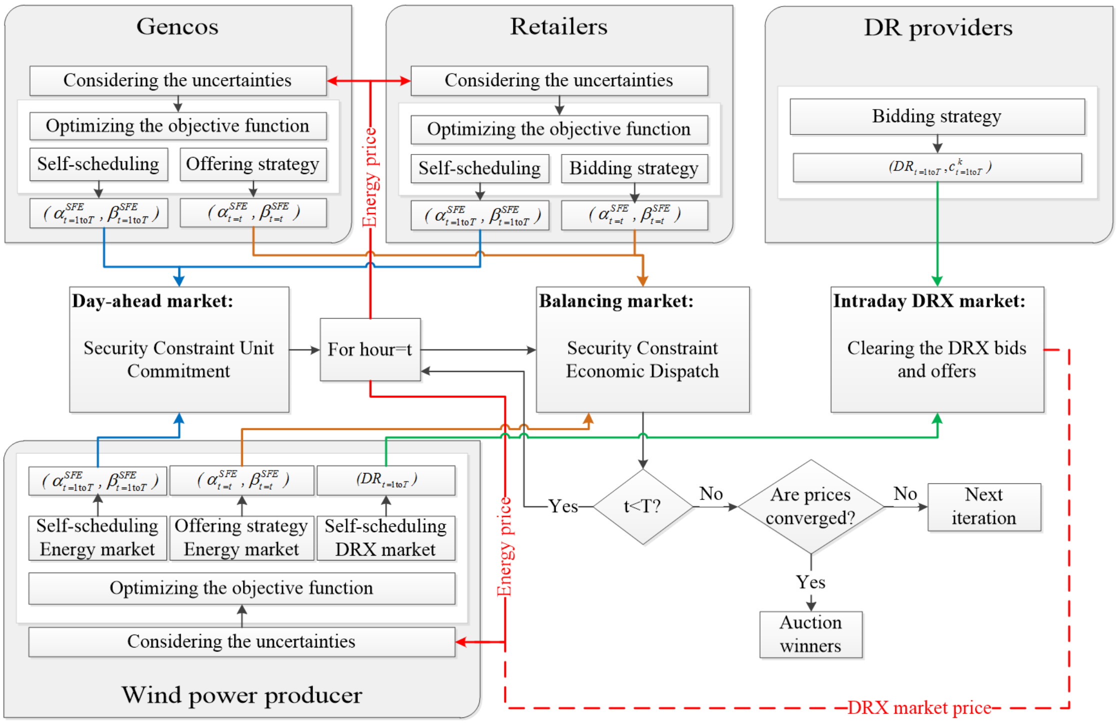

Fig. 2. The proposed WPP's model in oligopoly market.

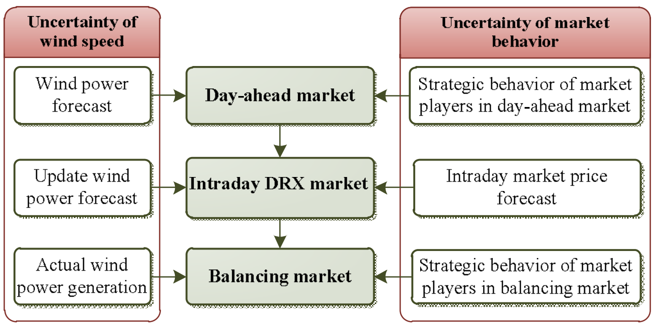

Fig. 3. The proposed multi-stage stochastic technique.

- In the third step, the won prices and quantities of the agents in each hour of the day-ahead market are known. In addition, the wind power forecast is updated. On this basis, WPP maximizes its profit by participating in the intraday DRX market through (9) and updated wind power data.

- In the fourth step, the won prices and quantities of the agents in each hour of the day-ahead and intraday markets are known. Although the wind power is updated in the intraday session, the decisions to participate in the balancing market are still unknown. On this basis, each agent maximizes its profit by obtaining the best balancing offer/bid in hour t by using (9), (16) or (24). To this end, the hourly offered prices and quantities of the day-ahead and intraday markets are considered known.

- In the fifth step, the ISO considers the agents' offers and bids to the balancing market in hour t and maximizes the social welfare using the SCED program by (26). The output of this step is the won auctions and prices of the balancing market for hour t.

V. Uncertainty Characterization

In this paper, two major sets of uncertainty are considered, namely wind power uncertainty and market uncertainty. In the IDRX market, where the WPP is a price-taker, prices of the mentioned market are considered as stochastic variables.

In the DA and balancing markets, where the WPP is a price-maker, the behavior of market players is considered as another uncertainty. In order to model those uncertainties, cost/revenue functions of market players are also considered as stochastic variables. Modeling the above mentioned uncertainties is expressed hereafter.

A. Wind power uncertainty modeling

The distribution function of wind speed is usually considered using a Weibull distribution [33]. The probability distribution function of wind speed can be utilized to obtain the wind power produced, P^{GW}. Based on this, the output power can be obtained through (32).

$$P^{GW} = \begin{cases} P_r & V_r \le WS_\omega \le V_{co} \\ P_r\left(A + B \times WS_\omega + C \times WS_\omega^2\right) & V_c \le WS_\omega \le V_r \\ 0 & other\ values \end{cases} \quad (32)$$

where WS_ω denotes the wind speed of scenario ω obtained from the probability distribution function. A, B, and C are constants that can be calculated according to [33]. V_c , V_{c0} and V_{cr} represent cut-in, cut-out and rated speeds, respectively. Different realizations of the wind power generation are modeled using the scenario generation process based on RWM [34]. At first, the distribution function is separated into several class intervals. Afterwards, each interval is related to a certain probability achieved by the PDF.

Consequently, due to the various intervals and the mentioned probabilities, RWM is utilized to generate hourly scenarios, as in [34].

B. IDRX Market prices uncertainty modeling

The IDRX market prices are characterized by log-normal distribution in each hour [35].

The probability density function of market prices is represented by (33). RWM technique is also applied for scenario generation in each hour.

$$f_p(\lambda,\mu,\sigma)=\frac{1}{\lambda\sigma\sqrt{2\pi}}\exp\left[-(\ln\lambda-\mu)^2/2\sigma^2\right] \quad (33)$$

where μ and σ represent the mean value and standard deviation, respectively.

C. Uncertainty of competitors' cost/revenue functions

In addition to wind power, strategic behavior of a WPP relies on the behavior of other market participants. Incomplete information about market participants' cost/revenue functions causes the WPP to be unable to simply predict their behavior in the market. It should be noted that the range of the mentioned functions is achievable [36], so WPP can estimate coefficients of cost/revenue functions. However, realizing accurate cost/revenue functions is impossible and the WPP should decrease risk of the unreliable estimation.

In order to decrease the risk of estimation error, the WPP should consider some deviations for the estimated amount. On this basis, different scenarios are generated to cover the estimation errors by using RWM. Since estimation errors regularly have a distribution very close to the normal [37], this paper carries out a scenario generation by Normal distribution. On this basis, the value and the probability of each scenario is associated to mean value, μ , and the standard deviation, σ , of the estimated coefficient.

D. Stochastic programming approach

In order to consider the impact of the two sources of uncertainty mentioned previously on the strategic behavior of the WPP, they have been characterized as stochastic procedures and the problem has been solved using a bi-level stochastic programming approach.

In the proposed approach, each level denotes a market horizon as illustrated in Fig. 3. The classification of the decision variables in each stage is presented as follows:

1) The first stage (*here-and-now*) stochastic decision variables are ($IC_{i,k,\omega}$, $c_{i,\omega}$, $e_{j,\omega}$, $f_{j,\omega}$, $D^{DA}_{j,t,\omega}$, $I_{i,t,\omega}$, $P^{DA}_{t,\omega}$, $P^{DA}_{i,t,\omega}$, $P^{Res}_{i,t,\omega}$, $P^{Sch}_{t,\omega}$, $y_{i,t,\omega}$, $z_{i,t,\omega}$, $SR_{t,\omega}$, $\lambda^{DA}_{t,\omega}$ and $\lambda^{Res}_{t,\omega}$).

In the first stage, the WPP designs the hourly offering strategy and submits it to the DA energy and reserve markets. In this stage, the source of decision is the probable realization of the stochastic events containing market players' behavior, wind power and prices of IDRX and balancing markets.

2) Stochastic variables ($CDRP_{d,t,\omega}$, $DR_{d,t,\omega}$ and $q^k_{d,t,\omega}$) are the second stage (*wait-and-see*) variables.

In the second stage, the WPP submits its offering strategy to the IDRX market when price and quantity of DA market are known.

In this stage, actual price and quantity of the IDRX and balancing markets and actual market players' behavior are still unknown. The WPP may realize new information and thus it can update the DA offers between closures of the DA market and IDRX one. On this basis, the WPP can update its wind power forecast to reduce the deviation between the newest forecast and the DA offer. It is important to note that, intraday market prices and coefficients of cost/revenue functions of market players are assumed to be stationary stochastic parameters. In other words, the scenario generation of the mentioned parameters is accomplished according to the trading stage just for once; whereas, the wind power is taken into account as a dynamic stochastic parameter, hence it can be updated in each trading stage. Therefore, the wind power scenarios are generated by different standard deviations associated with the stage. It reflects the higher forecasts' precision because of the closer stage to the balancing market.

3) The third stage (*realization*) stochastic decision variables are ($W_{t,\omega}$, $D^{RT}_{j,t,\omega}$, $P^{RT}_{t,\omega}$, $\Delta_{t,\omega}$, $\Delta^+_{t,\omega}$, $\Delta^-_{t,\omega}$ and $\lambda^{RT}_{t,\omega}$).

In this last stage, actual price and quantity of IDRX market, price of the balancing market, marker players' behavior and wind power are known. In addition, the hourly deviation incurred by the WPP is obtained and consequently the imbalance cost is calculated. When wind power is higher than its predicted amount in the second stage, downward regulation service is imposed on the system. Therefore, the WPP has to sell the excess of its generation at a price lower than the one of DA market. In contrast, when wind power is lower than the predicted amount, upward regulation service is imposed on the system. To this end, the WPP has to compensate its shortage at a price higher than the one of the DA market.

VI. Numerical Studies

The proposed model has been evaluated by using a modified IEEE 30-bus test system consisting of one 50 MW wind farm on Bus 5, 4 thermal plants, 21 demand nodes and 41 branches. The wind data and price of intraday market employed for the scenario generation process have been obtained from hourly data of Spanish electricity market in February 2010 [38]. Based on the *wait and see* technique, different wind power series are obtained for DA, intraday and balancing horizons.

The intervals between minimum and maximum amount of the uncertain parameters for DA and intraday markets are shown in Figs. 4 and 5, respectively. Moreover, three retailers have been added to this system to retail the electricity to consumers. The data of generation units and the retailers' coefficient data are presented in Appendix. Furthermore, three DRPs with equal market share are considered to aggregate local customers and offer their DR to the pool based IDRX market.

In this paper, it is assumed that each DRP can offer a three-step pair of quantity-price to the IDRX market in each hour. In order to obtain the mentioned pair, intraday market price has been employed. To this end, in all scenarios, the DRPs' offer to the IDRX market is assumed to be a ratio of intraday price, as shown in the Appendix.

It should be mentioned that the role of DRPs can be played by the mentioned retailers.

However, in order to clear the role of each player in the electricity market, the tasks of DRPs and retailers have been completely separated into two independent groups of market participants.

WPP participates in the IDRX market as a price-taker to cover its unexpected wind generation shortages. The price-taker assumption of WPP in IDRX market is due to the fact that DRX markets are essentially local markets comprising small capacity resources. Thus, a completely competitive market does not seem unreasonable here. Since the proposed IDRX market has not been implemented in real-world power systems, and in order to overcome the lack of input data, a typical load curve has been applied based on the real Spanish power system to illustrate the hourly available capacity of DRPs for participating in the IDRX market. To this end, DRP 1 offers prices equal to 40%, 70% and 100% of intraday market prices, respectively, related to 25%, 75% and 100% of total demand response. These offered prices for DRP 2 are equal to 50%, 80% and 110% of intraday market prices. Similarly, DRP 3 offers IDRX prices equal to 60%, 90% and 120% of intraday prices. The DRPs price-quantity offers are presented in the Appendix. It should be noted that, intervals 1 to 9am, 10am to 7pm and 8 to 12pm have been respectively considered as low load, off-peak, and peak periods.

In order to investigate the impact of the proposed model, the LMPs of Bus 5 achieved from two cases have been compared, namely by considering WPP as a price-taker in DA and balancing markets, and by considering WPP as a price-maker in the mentioned markets. The LMPs have been presented in Figs. 6 to 8. As it can be seen from Figs. 6 to 8, when the WPP is a price-taker in DA and balancing markets, it is required to purchase more amount of DR from IDRX market to insure its profit. Because of the increase of DR request, the price of IDRX market increases. In addition, the average of LMPs in both DA and balancing markets is increased because of the market power of the WPP.

According to that market power, in some hours (e.g., hours 5 and 6) a price-maker WPP prefers to increase the prices of DA and balancing market in order to increase its profit.

In order to show the effect of IDRX market on WPP's profit, the results obtained from two cases, namely without IDRX market and with the mentioned market, have been presented in Figs. 9 and 10, respectively.

The imbalance ratios are considered equal to 1.2 and 0.8. The amount of β is assigned to 0, which is related to a risk-taker WPP. It can be seen that by participating in the IDRX market it gives the opportunity for the WPP to significantly increase the balancing profit in most of the hours and accordingly to increase its total profit.

The effect of DRP participation level in the IDRX market on WPP's profits is presented in Table I. By increasing the participation of DRPs, the WPP prefers to participate in the IDRX market and modify its offers.

As it can be seen that, implementation of DRPs implies a significant increase in the WPP's expected profit. Except this initial increase, DRP participation level has an insignificant impact on the expected profit. The reason is that, the impact of the capacity of IDRX market on the WPP's profit is decreased due to WPP's installed capacity.

Therefore, the tendency of WPP for participating in the IDRX market is saturated. In Table II, the proposed model has been compared with the existing models in the literature from WPP's point of view.

The platform that has been utilized to assess the proposed model is a 64-bit Workstation with two Xeon E5-2687W 8C 3.10 GHz processors with 256 GB of RAM and an interface of MATLAB R2013b (8.2.0.701) and GAMS 24.0.2 has been employed.

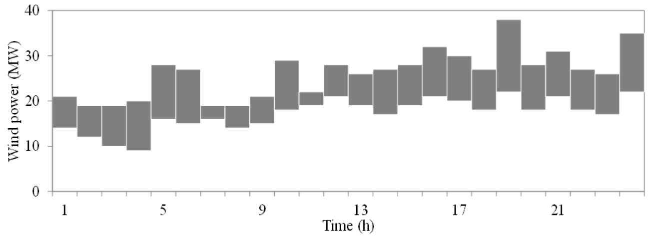

Fig. 4. Wind power intervals in day-ahead horizon.

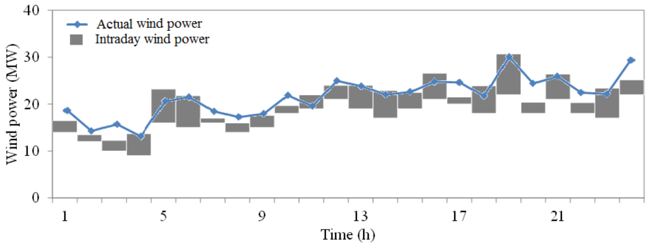

Fig. 5. Wind power intervals in intraday and balancing horizons.

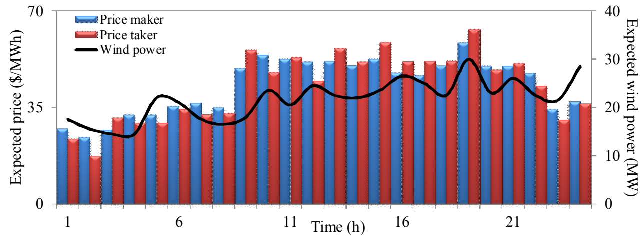

Fig. 6. DA market price.

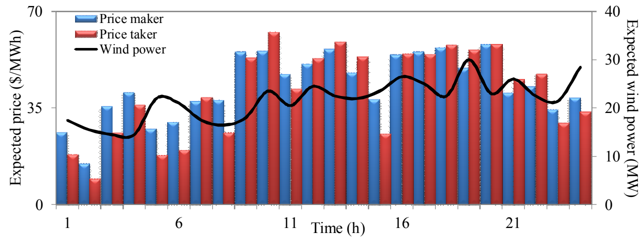

Fig. 7. Balancing market price.

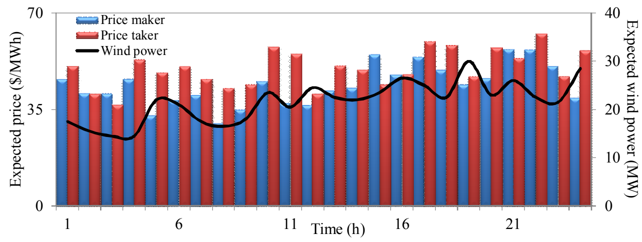

Fig. 8. IDRX market price.

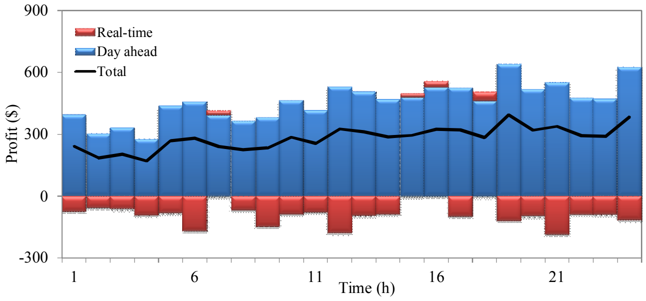

Fig. 9. WPP's profits without participating in the IDRX market.

TABLE I
EFFECT OF DRP PARTICIPATION LEVEL ON WPP'S COSTS AND REVENUES

DRP participation levels	0%	10%	20%	30%
Day ahead market profit ($)	11010.12	12606.45	12901.00	13022.87
Balancing market profit ($)	-2042.40	1712.92	1782.40	1791.10
Positive imbalance revenue ($)	101.47	219.65	222.50	224.20
Negative imbalance cost ($)	2309.70	1225.81	1233.80	1237.60
IDRX market profit ($)	0.00	-2600.62	-2670.20	-2689.90
CVaR ($)	6237.30	10165.10	10374.62	10403.60
Expected total profit ($)	6759.49	10712.59	11001.90	11110.67

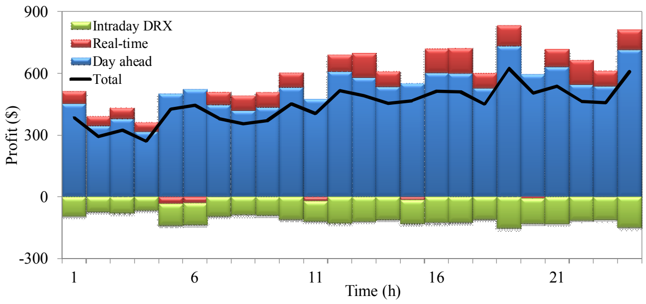

Fig. 10. WPP's profits by participating in the IDRX market.

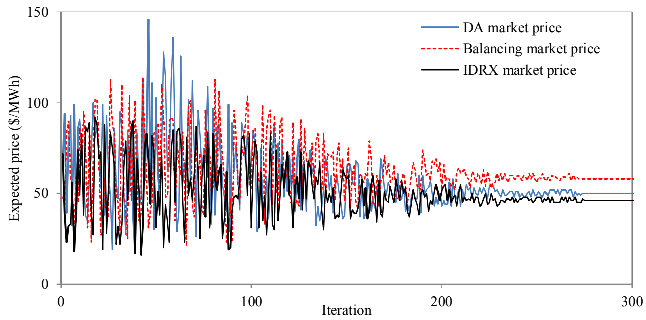

Fig. 11. Trend of market prices in different iterations at hour 20.

TABLE II
COMPARISON BETWEEN THE PROPOSED MODEL AND THE REPORTED MODELS IN THE LITERATURE FROM WPP'S POINT OF VIEW

	[23]	[21]	[22]	[24]	Proposed model
Considered markets	DA market	DA market, balancing market	DA market, balancing market	DA market, intraday market, balancing market	DA market, intraday market, balancing market
WPP modeling in the markets	WPP is modeled as a price-taker, price-maker, and REFIT	Price-maker in DA market and deviator in balancing market	Price-taker in DA market and Price-maker in balancing market	Price-taker	Price-maker in DA and balancing market
Objective function	Profit maximization	Expected profit maximization	Revenue maximization	Expected profit maximization	Expected profit maximization
Modeling approach	Deterministic MILP optimization	Stochastic Bi-level MPEC optimization	Stochastic Bi-level MPEC optimization	Stochastic MILP optimization	Stochastic Bi-level MILP optimization
Considered uncertainties	No uncertainty	Wind generation, balancing market price	DA market price, wind generation, system deviation	DA market price, wind generation, intraday market price	Wind generation, IDRX market price, competitors' cost/revenue functions
Risk management	No	No	No	CVaR index	CVaR index
Demand response consideration	-	Elastic demand	-	IDRX consideration	IDRX consideration, retailer modeled
Test system	No network model	IEEE 24-bus and IEEE 118-bus	No network model	No network model	IEEE 30-bus
Power flow	-	DC power flow without network losses	-	-	AC power flow with network losses
Contingency consideration	No	No	No	No	Yes (contingency on the lines by SCUC)
Platform	a Dell PowerEdge R910x64 computer with 4 processors with 1.87 GHz and 32 GB of RAM.	a Linux-based server with 4 processors with 2.9 GHz and 250 GB of RAM.	a laptop equipped with a 4-core processor with 2.66 GHz.	Not mentioned	a 64-bit Workstation with two Xeon E5-2687W 8C 3.10 GHz processors with 256 GB of RAM
Software solver	MATLAB and GAMS	CPLEX 12.2.0.1	CPLEX 12	CPLEX 12.5.0.0	MATLAB and CPLEX 12
Computation time	Approximately 3 minutes for all simulations	15.28 seconds for IEEE 24-bus, 48.43 seconds for IEEE 118-bus	1680 seconds	Not mentioned	109 seconds

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2015.2472339, IEEE Transactions on Industrial Informatics

Fig. 11 indicates the trend of market prices in different iterations at hour 20:00 (as an example), in case that a price-maker WPP is considered. As it can be seen, on the way to market convergence, high deviations of market prices occur. In this regard, DA market price increases to about three times more than its settled amount in the equilibrium point, while the balancing and IDRX market prices increase to twice more than those in the converged point. On this basis, the proposed model enables market operators to be aware of the dynamics of the convergence of market interactions.

According to Table II, main reason of higher computation time of the proposed model is arisen from considering contingencies of network by using SCUC. In addition, on contrary of the previously reported models, in this paper, the network is modeled by using a precise AC power flow.

VII. Conclusions

This paper presented a bi-level stochastic programming approach to derive the optimal offering strategy for a WPP in an oligopolistic electricity market, including day-ahead, intraday and balancing markets. Moreover, a novel local trading market in intraday timeframe was proposed, called IDRX market, in which WPP could cover offering deviations in an effective way. The strategic behavior of other market participants was also modeled through incomplete information game theory. In addition, the uncertainty of wind power generation and IDRX market prices were considered using a set of plausible scenarios. Simulation results showed that the WPP's profit resulting from the balancing market could be significantly increased by participating in the IDRX market. Modeling the WPPs in high penetration of wind power as price-makers reflected the capability of this market player to directly affect market prices, while considering WPPs as price-takers can be equivalent to ignoring this capability. On this basis, the proposed model increased the accuracy of modeling of WPPs in the market with high penetration of wind power, and consequently the ISO/the regulatory body can be aware about WPPs' capability and arrange policies, rules and regulations to avoid/mitigate the potential of market power.

Appendix

Table A.1
DRPs' Price offer to IDRX market ($/MWh)

	k	1	2	3
	q_{dt}^{k}	25% of total response	75% of total response	100% of total response
Base load	c_{1t}^{k}	6.86	12.01	17.15
	c_{2t}^{k}	8.58	13.72	18.87
	c_{3t}^{k}	10.29	15.44	20.58
Off peak	c_{1t}^{k}	11.41	19.96	28.52
	c_{2t}^{k}	14.26	22.82	31.37
	c_{3t}^{k}	17.11	25.67	34.22
Peak	c_{1t}^{k}	13.28	23.24	33.20
	c_{2t}^{k}	16.60	26.56	36.52
	c_{3t}^{k}	19.92	29.88	39.84

Table A.2
Generation units' data

Genco	a (MBtu /MW^{2}h)	b (MBtu /MWh)	c (MBtu)	Start-up (MBtu)	P_{max} (MW)	P_{min} (MW)	Min down/up (h)	Ramp (MW/h)
1	μ=0.01532	μ=12.5	μ=199.1	μ=566	84	25	6/6	30
	σ=2	σ=2	σ=2	σ=2				
2	μ=0.00889	μ=12.4	μ=275.6	μ=953	95	34	4/1	70
	σ=1	σ=1	σ=1	σ=1				
3	μ=0.01508	μ=16.2	μ=133.9	μ=596	85	15	1/1	50
	σ =0.5	σ =0.5	σ =0.5	σ=0.5				
4	μ=0.00208	μ=13.9	μ=209.5	μ=775	80	39	1/2	65
	σ=2	σ=2	σ=2	σ=2				

Table A.3
Retailers' coefficient data

Retailer	1	2	3
e ($)	μ=380, σ=2	μ=390, σ=1	μ=370, σ=0.5
f ($/MWh)	μ=-0.10, σ=2	μ=-0.15, σ=1	μ=-0.12, σ=0.5

Table A.4
WPP's data

Maintenance/operation cost ($/MWh)*	Investment cost ($/h)**	P_{max} (MW)	P_{min} (MW)
4	658	50	0

* Maintenance/operation cost of wind turbine equals to 35 $/kW/year [39].
** The wind turbine investment cost equals to 1250 $/kW with useful life of 25 years [39].

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