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Strategic Wind Power Trading Considering Rival Wind Power Production

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Abstract—In an electricity market with high share of wind power, it is expected that wind power producers may exercise market power. However, wind producers have to cope with wind's uncertain nature in order to optimally offer their generation, whereas in a market with more than one wind producers, uncertainty of rival wind power generation should also be considered. Under this context, this paper addresses the impact of rival wind producers on the offering strategy and profits of a price-maker wind producer. A stochastic day-ahead market setup is considered, which optimizes the day-ahead schedules considering a number of foreseen real-time scenarios. The results indicate that strategic wind producer is more likely to exercise market power having a mid-mean or low-mean forecast distribution, rather than having a high-mean one. Furthermore, it is observed that its offering strategy varies considerably depending on the rival's wind generation, given that its own expected generation is not high. Finally, as anticipated, expected system cost is higher when both wind power producers are expected to have low wind power generation.

Index Terms—Wind power, strategic offering, trading, two-stage market, day-ahead, MPEC.

Indices:

ω Index for scenarios generated based on strategic wind producer's forecast (referred to as SW).
 s Index for scenarios generated based on rival wind producer's forecast (referred to as RW).
 i Index for conventional units.
 d Index for demands.

Sets:

Ω Set of strategic wind producer's scenarios.
 S Set of rival wind producer's scenarios.
 I Set of conventional units.
 D Set of demands.

Parameters:

\bar{P}_d^D Quantity bid of demand d [MW].
 \bar{P}_i^G Quantity offer of unit i [MW].
 $P_\omega^{F,SW}$ Wind power forecast of strategic wind producer under scenario ω [MW].
 $P_s^{F,RW}$ Wind power forecast of rival wind producer under scenario s [MW].

λ_i^G Offer price of unit i [\$/MWh].
 λ_i^U Offer price for upward reserve of unit i [\$/MWh].
 λ_i^D Offer price for downward reserve of unit i [\$/MWh].
 γ_ω Probability of scenario ω .
 π_s Probability of scenario s .
 R_i^U Upward reserve capacity of unit i [MW].
 R_i^D Downward reserve capacity of unit i [MW].
 V_d^{shed} Value of lost load for demand d [\$/MWh].

Day-ahead Variables:

λ_s^{DA} Day-ahead market-clearing price under scenario s [\$/MWh].
 $p_{i,s}^G$ Day-ahead dispatch of unit i under scenario s [MW].
 $p_s^{\text{DA},SW}$ Day-ahead dispatch of strategic wind producer under scenario s [MW].
 $p_s^{\text{DA},RW}$ Day-ahead dispatch of rival wind producer under scenario s [MW].
 $p^{\text{Of},SW}$ Quantity offer of strategic wind producer [MW].

Real-time Variables:

$\lambda_{\omega,s}^{\text{RT}}$ Probability-weighted real-time market-clearing price under scenario ω and scenario s [\$/MWh].
 $p_\omega^{\text{spill},SW}$ Wind power spillage under scenario ω for strategic wind producer [MW].
 $p_{\omega,s}^{\text{spill},RW}$ Wind power spillage under scenario ω and scenario s for rival wind producer [MW].
 $r_{i,\omega,s}^U$ Upward reserve deployed by unit i under scenario ω and scenario s [MW].
 $r_{i,\omega,s}^D$ Downward reserve deployed by unit i under scenario ω and scenario s [MW].
 $l_{d,\omega,s}^{\text{shed}}$ Involuntarily load shed of demand d under scenario ω and scenario s [MW].

I. INTRODUCTION

In recent years, a lot of attention is drawn on wind power and its impact on electricity markets. Political decisions as well as technological advances mitigating climate change, have led to an increased penetration of wind power in energy systems, transforming wind power producers into dominant market players. For example, the mix of energy generation is rapidly changing in many countries, such as Denmark, Spain and Germany, where wind power generation is holding an increasing share of the total power generation. Under this context, benefits and premiums for wind power generation are not anymore the case in many countries and wind power producers are forced to compete under the same rules with conventional ones [1], being able, in some cases, to exercise market power in order to increase profits. However, uncertainty and variability in wind power production pose operational challenges in electricity markets, for both power producers and market operators. The cost for backup reserves is considerably high in order to guarantee reliability, while energy storage is still not mature enough [2]. Therefore, intensive research in wind power forecasting, as for example presented in [3], has led to mature forecasting tools, which are used widely in the related decision-making processes. Furthermore, advanced stochastic optimization as well as game theory are deployed by researchers in the technical literature, in an effort to address the problem of wind power trading under uncertainty in liberalized energy markets.

Initial studies adopted models where wind power producers are non-strategic players, i.e., price-takers, and/or receiving additional support when participating in a forward electricity market [4]–[7]. However, as the cost of wind power production is low and the competitiveness of wind power increases, wind power producers are forced to participate in the electricity markets under full competition and following the same rules as conventional producers [8]. Under this context, in [9], it is considered that wind power producers strategically offer their power in the balancing market. It is anticipated that due to large volumes of traded energy in day-ahead market, wind producer acts as a price-taker there. The authors also investigate how the shape of the forecast distribution impacts the offering strategy of producer. The problem of a price-maker wind power producer in the day-ahead market, being a deviator in the balancing market, was later addressed in [10]. More specifically, the problem was formulated as a stochastic optimization tool for market participation, where uncertainty pertaining to wind power production is represented through scenarios. The impact of a price-maker wind power producer on electricity prices as well as on the resulted imbalances is studied in [11], for a market without regulated tariffs. Furthermore, study [12] additionally considered, through scenarios, the uncertainties in demand, wind power generation and bidding strategies of strategic conventional generators focusing on the problem of strategic wind power trading. Recent study [13], proposes a multi-stage risk-constrained stochastic complementarity model to derive the optimal offering strategy of

a wind-power producer that participates in both the day-ahead and the balancing markets. Uncertainties concerning wind-power production, market prices, demands' bids and rivals' offers are modeled in this study using a set of scenarios.

Aforementioned studies focus on a single strategic wind power producer and its strategic offering problem since, as highlighted in [13], there are countries where even a single wind power producer owns large enough wind capacity that enables him to behave strategically. However, it can naturally be argued that this setup, including only one strategic stochastic producer, is rather unrealistic. The consideration of more than one strategic stochastic producers would lead to a game-theoretic approach, which is a problem generally hard to cope with. Moreover, given that each producer owns its private wind power forecast, the problem would lead to a game under incomplete information, yielding a bayesian approach. Motivated by the above challenges, in [14] authors approach the problem of an electricity market with multiple stochastic producers based on a minority game, studying the competition among them using a set of learning tools to identify their actions. Under the same context, the contribution of this paper is to address the impact of additional wind power producers on the wind power offering strategy of a price-maker wind power producer. In this approach, avoiding a more complex setup, i.e., an equilibrium program with equilibrium constraints (EPEC), rival wind power production is represented by a number of foreseen scenarios followed by the corresponding probabilities. In parallel, various levels of wind power generation for both wind power producers are considered, investigating their impact on producer's offering strategy and profits, as well as on market outcomes. The problem is formulated as a bilevel stochastic optimization model, following a complementarity approach [15].

The rest of the paper is organized as follows: Section II presents the mathematical formulation of the problem. Section III presents the results for a case-study and, lastly, Section IV concludes the paper.

II. MATHEMATICAL FORMULATION

A. Model Assumptions and Uncertainty Characterization

A pool-based electricity market is assumed, where producers submit power and price offers for the day-ahead (DA) and real-time (RT) markets. The assumed DA market-clearing mechanism is a two-stage stochastic optimization program, as presented in [16], which co-optimizes DA and RT markets and enables better operational results in markets with considerable sources of uncertainty. In the investigated framework, two main sources of uncertainty are considered, namely:

- wind power generation of investigated strategic wind producer,
- wind power generation of rival wind producer,

both of which are introduced as independent wind power scenarios. Note that in contrast to [10], real-time price scenarios are driven by the optimization model. Furthermore, the approach of this paper differs from [9], [10], [12], [17] in

the sense that it considers the uncertainty of rival wind power producer.

An imperfectly competitive electricity market is considered, in which the wind producers and conventional units may offer strategically [18], [19]. In line with [9]–[12], we assume that the wind producer perfectly knows the offering strategy of its conventional rivals. Consideration of multiple strategic wind producers with different private forecasts, would lead to a non-cooperative game with incomplete information, which is our future extension. Similarly to [9], [11], [19], and for the sake of simplicity, transmission constraints are not enforced. In addition, the inter-temporal constraints, e.g., ramping limits of conventional units, are not enforced and thus a single-hour auction is considered. The operational cost of wind power producers is negligible since they are not incurred by the fuel costs. In some realistic electricity markets, this cost is even negative due to renewable incentives [20]. As it is customary in the technical literature, e.g., [21]–[25], we assume that the wind production cost is zero. Finally, demand is assumed to be deterministic and inelastic to price.

B. Bilevel Model

The offering strategy of the strategic wind power producer is modeled through a stochastic complementarity approach [10], [15]. We use a bilevel model, i.e., (1)-(2), whose upper-level (UL) problem (1) maximizes wind producer's expected profit, and lower-level (LL) problem (2) clears the stochastic two-stage market through minimizing the expected system cost. The UL objective function is constrained by both UL constraint (1b) and LL problem (2). Dual variables are indicated in each LL constraint after a colon. Note that in model (1)-(2), the strategic wind producer's scenarios for its own generation are indicated by $\omega \in \Omega$ and for its rival's by $s \in S$.

$$\begin{aligned} & \text{Maximize}_{p^{\text{Of,SW}}, \Xi^{\text{LL,P,U}} \Xi^{\text{LL,D}}} \\ & \sum_{s \in S} \pi_s \left[\lambda_s^{\text{DA}} p_s^{\text{DA,SW}} + \sum_{\omega \in \Omega} \lambda_{\omega,s}^{\text{RT}} (P_\omega^{\text{F,SW}} - p_s^{\text{DA,SW}} - p_\omega^{\text{spill,SW}}) \right] \end{aligned} \quad (1a)$$

subject to

$$p^{\text{Of,SW}} \geq 0 \quad (1b)$$

where λ_s^{DA} , $p_s^{\text{DA,SW}}$, $\lambda_{\omega,s}^{\text{RT}}$ and $p_\omega^{\text{spill,SW}} \quad \forall \omega, \forall s, \in$

$$\arg \text{Minimize}_{\Xi^{\text{LL,P}}} \left\{ \begin{aligned} & \sum_{i \in I} \lambda_i^{\text{G}} p_{i,s}^{\text{G}} + \sum_{\omega \in \Omega} \gamma_\omega \left[\sum_{i \in I} (\lambda_i^{\text{U}} r_{i,\omega,s}^{\text{U}} - \lambda_i^{\text{D}} r_{i,\omega,s}^{\text{D}}) \right. \\ & \left. + \sum_{d \in D} V_d^{\text{shed}} l_{d,\omega,s}^{\text{shed}} \right] \end{aligned} \right. \quad (2a)$$

subject to

$$\sum_{d \in D} \bar{P}_d^{\text{D}} - \sum_{i \in I} p_{i,s}^{\text{G}} - p_s^{\text{DA,SW}} - p_s^{\text{DA,RW}} = 0 : \lambda_s^{\text{DA}} \quad (2b)$$

$$0 \leq p_{i,s}^{\text{G}} \leq \bar{P}_i^{\text{G}} : \underline{\phi}_{i,s}, \bar{\phi}_{i,s} \quad \forall i \quad (2c)$$

$$0 \leq p_s^{\text{DA,SW}} \leq p^{\text{Of,SW}} : \underline{\sigma}_s^{\text{SW}}, \bar{\sigma}_s^{\text{SW}} \quad (2d)$$

$$0 \leq p_s^{\text{DA,RW}} \leq P_s^{\text{F,RW}} : \underline{\sigma}_s^{\text{RW}}, \bar{\sigma}_s^{\text{RW}} \quad (2e)$$

$$\begin{aligned} & \sum_{i \in I} (r_{i,\omega,s}^{\text{D}} - r_{i,\omega,s}^{\text{U}}) - \sum_{d \in D} l_{d,\omega,s}^{\text{shed}} - (P_\omega^{\text{F,SW}} \\ & - p_s^{\text{DA,SW}} - p_\omega^{\text{spill,SW}}) - (P_s^{\text{F,RW}} - p_s^{\text{DA,RW}} \\ & - p_\omega^{\text{spill,RW}}) = 0 : \lambda_{\omega,s}^{\text{RT}} \quad \forall \omega \end{aligned} \quad (2f)$$

$$0 \leq p_\omega^{\text{spill,SW}} \leq P_\omega^{\text{F,SW}} : \underline{\tau}_\omega^{\text{SW}}, \bar{\tau}_\omega^{\text{SW}} \quad \forall \omega \quad (2g)$$

$$0 \leq p_{\omega,s}^{\text{spill,RW}} \leq P_s^{\text{F,RW}} : \underline{\tau}_{\omega,s}^{\text{RW}}, \bar{\tau}_{\omega,s}^{\text{RW}} \quad \forall \omega \quad (2h)$$

$$0 \leq l_{d,\omega,s}^{\text{shed}} \leq \bar{P}_d^{\text{D}} : \underline{\psi}_{d,\omega,s}, \bar{\psi}_{d,\omega,s} \quad \forall d, \forall \omega \quad (2i)$$

$$0 \leq r_{i,\omega,s}^{\text{D}} \leq R_i^{\text{D}} : \underline{\mu}_{i,\omega,s}^{\text{D}}, \bar{\mu}_{i,\omega,s}^{\text{D}} \quad \forall i, \forall \omega \quad (2j)$$

$$0 \leq r_{i,\omega,s}^{\text{U}} \leq R_i^{\text{U}} : \underline{\mu}_{i,\omega,s}^{\text{U}}, \bar{\mu}_{i,\omega,s}^{\text{U}} \quad \forall i, \forall \omega \quad (2k)$$

$$r_{i,\omega,s}^{\text{U}} \leq (\bar{P}_i^{\text{G}} - p_{i,s}^{\text{G}}) : \bar{\mu}_{i,\omega,s}^{\text{PR}} \quad \forall i, \forall \omega \quad (2l)$$

$$r_{i,\omega,s}^{\text{D}} \leq p_{i,s}^{\text{G}} : \underline{\mu}_{i,\omega,s}^{\text{PR}} \quad \forall i, \forall \omega \quad (2m)$$

} $\forall s$,

where $\Xi^{\text{LL,P}} = \{p_s^{\text{DA,SW}}, p_\omega^{\text{spill,SW}}, p_{i,s}^{\text{G}}, r_{i,\omega,s}^{\text{U}}, r_{i,\omega,s}^{\text{D}}, l_{d,\omega,s}^{\text{shed}}, p_{\omega,s}^{\text{spill,RW}}\}$ is the set of primal variables of the LL problem. Furthermore, $\Xi^{\text{LL,D}} = \{\lambda_s^{\text{DA}}, \underline{\phi}_{i,s}, \bar{\phi}_{i,s}, \underline{\sigma}_s^{\text{SW}}, \bar{\sigma}_s^{\text{SW}}, \underline{\sigma}_s^{\text{RW}}, \bar{\sigma}_s^{\text{RW}}, \lambda_{\omega,s}^{\text{RT}}, \underline{\tau}_\omega^{\text{SW}}, \bar{\tau}_\omega^{\text{SW}}, \underline{\tau}_{\omega,s}^{\text{RW}}, \bar{\tau}_{\omega,s}^{\text{RW}}, \underline{\psi}_{d,\omega,s}, \bar{\psi}_{d,\omega,s}, \underline{\mu}_{i,\omega,s}^{\text{D}}, \bar{\mu}_{i,\omega,s}^{\text{D}}, \underline{\mu}_{i,\omega,s}^{\text{U}}, \bar{\mu}_{i,\omega,s}^{\text{U}}, \underline{\mu}_{i,\omega,s}^{\text{PR}}, \bar{\mu}_{i,\omega,s}^{\text{PR}}\}$ is the set of dual variables of the LL problem. Finally, the primal variables of the UL problem (1a)-(1b) are $p^{\text{Of,SW}}$ as well as all members of variable sets $\Xi^{\text{LL,P}}$ and $\Xi^{\text{LL,D}}$.

The UL objective function (1a) maximizes strategic wind producer's expected profit, considering wind power generation scenarios for rival wind producer ($s \in S$), and consists of:

- Wind producer's profit in DA market, being the product of DA market-clearing price, i.e., λ_s^{DA} , and scheduled quantity, i.e., $p_s^{\text{DA,SW}}$.
- Wind producer's expected profit/cost in RT market, being the product of the probability-weighted RT market-clearing price, i.e., $\lambda_{\omega,s}^{\text{RT}}$, and wind power excess/deficit in RT, i.e., $P_\omega^{\text{F,SW}} - p_s^{\text{DA,SW}} - p_\omega^{\text{spill,SW}}$.

The UL constraint (1b) imposes the strategic quantity offer of wind producer, i.e., $p^{\text{Of,SW}}$, to be non-negative. The LL objective function (2a) minimizes the expected system cost including generation-side costs in DA and RT as well as load shedding costs in RT. The LL constraint (2b) represents the power balance in DA, whose dual variable, i.e., λ_s^{DA} , provides the DA market-clearing price. Constraints (2c)-(2e) bind the DA schedule of conventional units and wind producers, based on their quantity offers (or expected generation for rival wind producer). Constraint (2f) refers to power balance in RT that adjusts the energy imbalance by operational reserve

TABLE I
TECHNICAL CHARACTERISTICS OF CONVENTIONAL UNITS

Unit (i)	P_i^G [MW]	λ_i^G [\$/MW]	R_i^U [MW]	λ_i^U [\$/MWh]	R_i^D [MW]	λ_i^D [\$/MWh]
G1	451	35.88	250	40	0	-
G2	500	30.12	200	35	0	-
G3	80	45.00	40	50	0	-
G4	300	5.00	300	7	300	2
G5	474	18.72	290	25	125	10
G6	800	20.56	300	27	200	12
G7	800	7.53	400	15	100	5

deployment, wind power spillage and load shedding. Note that its corresponding dual variable provides the probability-weighted RT market-clearing price, i.e., $\lambda_{\omega,s}^{RT}$. Constraints (2g)-(2h) imply that wind power spillage should be equal to or lower than the wind power realization. Constraint (2i) restricts the load shedding quantity. Operational reserves in RT are bounded by reserve quantity offers and DA dispatch through (2j)-(2m).

Given that LL problem (2) is continuous, linear and therefore convex, bilevel model (1)-(2) can be recast as a single-level mathematical program with equilibrium constraints (MPEC), by replacing the LL problem by its Karush-Kuhn-Tucker (KKT) optimality conditions [15]. The latter MPEC includes a number of non-linearities, thus we accommodate the strong duality theorem along with Big-M approach [26], [27] to linearize it, at the cost of introducing a set of auxiliary binary variables. Following this linearization approach, MPEC is transformed into a mixed-integer linear programming (MILP) problem, which can be solved with available solvers.

III. CASE-STUDY

A. Data

A case-study based on the IEEE one-area reliability test system [28] is considered, in which conventional units are grouped by type and price, similarly to [29]. Each conventional unit offers at a quantity identical to its installed capacity and at a price given in Table I. In addition to the conventional units, two wind power producers, i.e., the investigated strategic producer (indicated by SW) and its rival wind producer (indicated by RW), are considered with the same installed capacity of 800 MW each. The system load is 2850 MW, and its value of lost load is set to \$200/MWh.

In this paper, we investigate the market from the strategic wind power producer's viewpoint. In order for the strategic producer to optimally offer its wind power generation to the market, it needs an uncertainty forecast, e.g., in the form of wind power scenarios. There are numerous techniques in the technical literature to generate scenarios of wind power generation, such as [30]–[34]. In this study, strategic wind power producer needs to forecast wind generation of both its own wind units as well as its rival's. We assume that both

TABLE II
SHAPE PARAMETERS OF BETA DISTRIBUTIONS

Shape Parameters	Set 1 $a > b$	Set 2 $a \simeq b$	Set 3 $a < b$
(a, b)	(3.78,1.62)	(5.37,5.37)	(1.89,4.48)

wind power forecasts follow a Beta distribution with shape parameters (a, b) . Strategic wind producer generates 2000 scenarios for its own wind power generation and the same number of scenarios for its rival's based on the corresponding forecast distribution. Then scenarios are reduced to three in order to reduce computational cost, using a scenario reduction approach such as the K-means method [35]. Note that these samples are in per-unit, i.e., wind production divided by installed wind capacity. This procedure provides strategic wind producer's scenarios denoted by ω_1, ω_2 and ω_3 and, similarly, rival wind producer's scenarios s_1, s_2 and s_3 with their corresponding probabilities.

To evaluate the impact of rival's generation uncertainty on strategic producer's offering decisions, we investigate different levels of wind power generation for both producers. Therefore, three different sets for the parameters of Beta distribution are examined in this case-study, as given in Table II, which yield different distribution shapes for both producers. These sets are selected to represent the three cases with the most characteristic differences in distribution shapes, i.e., cases with high-mean, mid-mean and low-mean distributions, for each of the producers. The three sets correspond to shape parameters $a > b, a \simeq b$ and $a < b$ respectively. Thus, we investigate the impact of forecast distributions on the market outcomes as well as on strategic wind producer's profits, for all combinations of distribution shapes.

B. Results and Discussion

In this section, we present the results for the case-study assuming that each of the wind power producers can have high-mean, mid-mean or low-mean forecast distribution. Therefore, nine scenarios are investigated in total, with respect to their effect on strategic wind producer's profits and on market results.

In Fig. 1, one can see the expected profit of the strategic wind power producer for all the investigated cases. As expected, strategic wind power producer gains more profit when its expected production is high (blue curve). It is also observed that given a high-mean forecast distribution for its own production, its profit is independent of whether its rival has a high-mean or a mid-mean distribution. However, if the rival is expected to have low wind power generation, then strategic wind producer sees a considerable increase in its profits. On the other hand, if strategic wind producer has mid- or low-mean forecast distributions for its own production, then its profit increases as rival's production decreases.

The aforementioned results can be explained by observing Fig. 2 and 3, which present the wind power offers of strategic

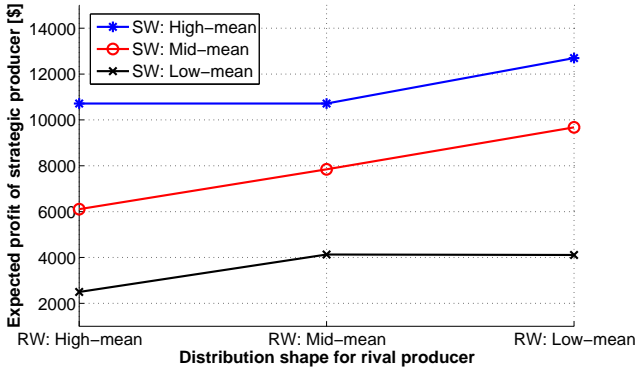


Fig. 1. Profit of strategic wind power producer

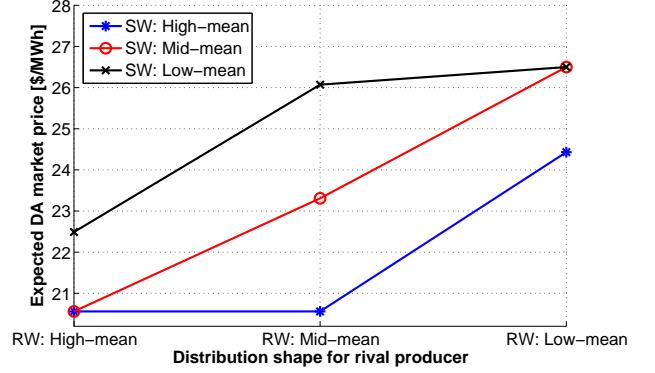


Fig. 3. The expected DA market-clearing price

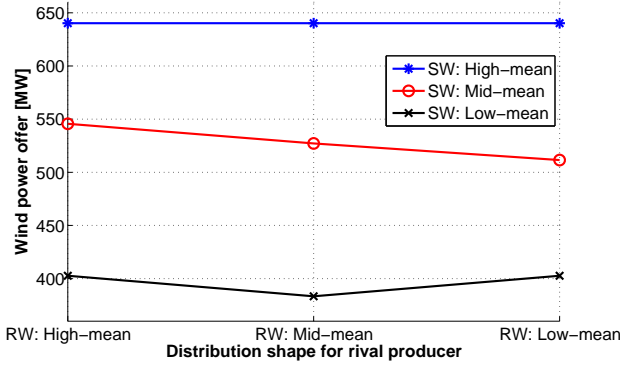


Fig. 2. The strategic wind producer's quantity offer to DA market

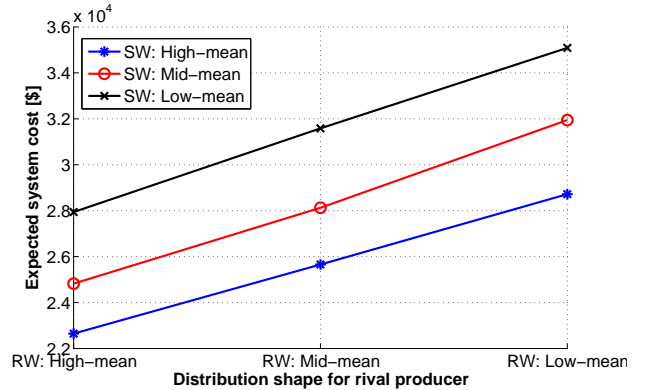


Fig. 4. The expected total system cost

wind producer and the expected DA prices, respectively. It is interesting to note in Fig. 2 that the optimal offering strategy, depends highly on rival's forecast distribution and, thus, it is different for each distribution shape of the rival producer. More particularly, under high-mean forecast distribution (blue curve), strategic wind producer offers the same quantity of power to the market, independently of rival's forecast distribution. However, given a low-mean distribution for the rival producer, expected DA price is considerably higher, which explains the increased profits for that case as seen in Fig. 1. On the other hand, given a mid-mean forecast distribution (red curve) for strategic producer, its offers decrease as the rival's expected generation decreases. In that case, even if the forecast for its own generation is the same, the offering strategy is changing depending on rival's expectation and strategic producer exercises market power by withholding an amount of wind power as the rival's forecast decreases. For low-mean forecast distribution (black curve) the results are mixed, as strategic wind producer exercises market power only for mid-mean forecast distribution of the rival.

Finally, in Fig. 4 the total system cost, i.e., expected DA and RT system cost, is presented for the same cases as before. As anticipated, it is observed that the expected total system cost increases when the system is expected to have low total wind power generation. Therefore, when both producers have

low-mean forecast distribution the system cost is high and the opposite.

IV. CONCLUSION AND FUTURE PROSPECTS

As wind power producers become dominant market players in a number of electricity markets, it is expected that they offer their generation strategically. This paper addresses the impact of the uncertainty introduced by a rival wind producer, on the offering strategy of a price-maker wind producer. The price-maker wind power producer forecasts the generation of its rival and makes optimal power offers to a stochastic DA market. The results indicate that strategic producer exercises more market power for mid- or low-mean forecast distributions of its own generated wind power. It is observed that its offering strategy depends highly on the rival's expected generation, given that its own expected wind generation is not high. Additionally, in these cases strategic producer withholds a part of its generation in order to increase DA market prices on its own benefit. Finally, it is observed that the expected total system cost is, as anticipated, higher when both producers are expected to produce low wind power.

This study can be extended by assuming more than two strategic wind power producers in the market, where the wind power uncertainty can be represented by an aggregate forecast distribution. Furthermore, the consideration of all participating

wind power producers being price-makers, would yield a more complex study which could be formulated as a game of incomplete information, since individual wind power forecasts are not common knowledge. In the latter case bayesian Nash equilibrium is to be investigated.

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