Sharing Wind Power Forecasts in Electricity Markets: A Numerical Analysis

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Abstract—In an electricity pool with significant share of wind power, all generators including conventional and wind power units are generally scheduled in a day-ahead market based on wind power forecasts. Then, a real-time market is cleared given the wind power realization and fixed day-ahead decisions to adjust power imbalances. This sequential market-clearing process may cope with serious operational challenges such as severe power shortage in real-time due to erroneous wind power forecasts in day-ahead market. To overcome such situations, several solutions can be considered such as adding flexible resources to the system. In this paper, we address another potential solution based on information sharing in which market players share their own wind power forecasts with others in day-ahead market. This solution may improve the functioning of sequential market-clearing process through making more informed day-ahead schedules, which reduces the need for balancing resources in real-time operation. This paper numerically evaluates its potential value for the whole system in terms of system cost reduction. Besides, its impact on each market player’s profit is analyzed. The framework of this study is based on a stochastic two-stage market setup and complementarity modeling, which allows us to gain further insights into information sharing impacts.

Index Terms—Wind power, forecast sharing, two-stage market, day-ahead, real-time, MPEC, out-of-sample simulation

I. INTRODUCTION

O

VER the last decade, the share of wind power has rapidly grown. For example, wind power is the generating technology with the highest rate for new installations in Europe, reaching 128.8 GW of installed capacity [1]. Germany is currently the leading country in terms of installed capacity with more than 39 GW installed by the end of 2014, while Denmark is a pioneer country in terms of the high share of wind power production, covering the same year almost 40% of its electricity consumption from wind power [2]. However, uncertainty and variability in wind power production pose operational challenges in electricity markets. Under this context, wind power forecast and the level of its accuracy are key factors in modern power systems. This rises up a need for re-thinking the design of electricity markets as the share of stochastic non-dispatchable production increases.

The importance of wind power forecast accuracy for improving the functioning of wind-integrated power systems is investigated in a large number of papers and technical reports in the existing literature. Reference [3] gives an overview of the recent advances in wind power forecast techniques. Although such techniques are constantly improving, wind forecasts are still followed by a considerable error especially in day-ahead timescale [4]–[6]. This error leads to several operational challenges in electricity markets as addressed in [7]–[10]. One potential solution to cope with those challenges is to add various operational flexible resources to the market such as peaking units and demand-side management [11]. The operational value of those resources is evaluated in [12]–[14].

In this paper, we address another potential solution for system functioning improvement, i.e., sharing wind power forecasts among different players, which may assist system players to build a more accurate wind power distribution than the one they individually forecast. We consider a market with a single wind producer and several conventional units, cleared by a market operator. We assume that the wind producer and the market operator independently forecast day-ahead wind production. It is intuitively expected that sharing wind power forecasts between the wind producer and the market operator may yield improved social welfare (or reduced system cost) through generating a more qualified wind forecast distribution, though not necessarily at the benefit of each individual market player. This potential value is numerically evaluated in this paper from system’s perspective in terms of expected system cost, i.e., the total cost across all market players.

Under this context, we consider a short-run electricity market with two trading floors, i.e., day-ahead (DA) and real-time (RT) markets, which are cleared sequentially. The DA market is cleared based on the available wind power forecast in that market. Given the fixed DA decisions, the market operator clears RT market based on actual wind power realization, which might be different than the one considered in DA market. Two different setups are generally available to manage wind power uncertainty within a sequential DA-RT framework: deterministic and stochastic. In the first one, a deterministic (single-value) wind power forecast is considered but accommodating smarter market products, e.g., flexiramp [15]. In contrast, DA market is cleared stochastically in the second setup in which a number of potential wind power realizations are taken into account via scenarios [16]–[19]. In this paper, we use a stochastic market setup for two main reasons. Firstly, it better accommodates wind uncertainty by consider-
The proposed three-step evaluation framework is schematically depicted in Fig. 1 and explained in detail as follows:

Step 1) This step models the profit-maximization of wind power producer and derives its strategic quantity offer to be submitted in DA market.

Step 2) Given the quantity offer of the wind producer in Step 1, the market operator stochastically clears DA market considering all potential operating conditions in RT (via scenarios).

Step 3) Given the DA schedules in Step 2, the RT market is cleared for a large number of wind power realization scenarios, which are not necessarily the same with numerical results for a large-scale case study based on the IEEE one-area reliability test system. Finally, Section IV concludes the paper.

II. Evaluation Framework

A. Features and Assumptions

A stochastic market clearing model based on a two-stage auction (DA and RT) is considered, which appropriately captures wind power uncertainty and different forecast distributions. For the sake of simplicity and to make findings more intuitive, transmission constraints are not enforced. However, a network-constrained model is a straightforward extension [17]. The inter-temporal constraints, e.g., ramping limits of thermal units, are not enforced and thus a single-hour auction is considered. In order to avoid problem complexity, a single wind producer is considered. However, a problem with several wind producers is our future extension. The wind producer is assumed to be a strategic producer since sharing forecasts may bring market power to such a producer. Instead, all conventional producers are assumed to be competitive, which implies that sharing wind power forecasts between wind producer and market operator does not bring market power to those producers. We assume that the wind producer behaves strategically only in terms of its quantity offer. In contrast, it behaves competitively in terms of price offer, which is equal to its marginal cost, i.e., zero. To avoid non-convexities, the binary commitment decisions of conventional producers are not modeled. Finally, demand is assumed to be deterministic and inelastic to price.

B. Proposed Three-step Framework

The rest of the paper is organized as follows: Section II proposes a three-step evaluation framework and provides the corresponding mathematical formulations. Section III provides numerical results for a large-scale case study based on the IEEE one-area reliability test system. Finally, Section IV concludes the paper.
wind producer’s or market operator’s forecasts in DA (out-of-sample simulation).

Note that scenarios involved in Steps 1 and 2 are generated based on available wind power forecasts in DA market, while Step 3 is solved based on actual realizations in RT.

The aforementioned three-step framework is investigated for two different analyses. The first analysis (so-called non-sharing analysis) considers that the wind power producer and the market operator use their own forecasts which may follow different distributions. Therefore, different sets of scenarios are considered in Steps 1 and 2. The second analysis (so-called sharing analysis) considers that the market operator and wind producer share their forecast information and, therefore, the decisions of the first and second steps are made based on an identical set of scenarios.

The proposed three-step framework is mathematically explained in the following subsections.

C. Step 1: Strategic Offering of the Wind Producer

The symbols used in the section are listed below. Note that superscript (1) within all variables and stochastic parameters refers to Step 1.

NOTATION:

Sets:
\[ \Omega \] Set of wind producer’s scenarios
\[ I \] Set of conventional units
\[ D \] Set of demands
Indices:
\[ \omega \] Index for scenarios generated based on wind producer’s own forecast
\[ i \] Index for conventional units
\[ d \] Index for demands

DA Variables:
\[ \lambda^{DA,(1)} \] DA market-clearing price [$/MWh]
\[ p_{WDA,(1)} \] Scheduled wind power [MW]
\[ p_{Wof,(1)} \] Quantity offer of wind power producer [MW]
\[ p_{i,(1)} \] Power scheduled for the \( i \)th conventional unit [MW]
\[ C^{(1)} \] Expected system cost [$]

RT Variables:
\[ \lambda^{RT,(1)} \] Probability-weighted RT market-clearing price under scenario \( \omega \) [$/MWh]
\[ p_{\text{spill},(1)} \] Wind power spillage under scenario \( \omega \) [MW]
\[ p_{U,(1)} \] Reserve-up deployed by the \( i \)th conventional unit under scenario \( \omega \) [MW]
\[ p_{D,(1)} \] Reserve-down deployed by the \( i \)th conventional unit under scenario \( \omega \) [MW]
\[ V_{d,\omega}^{\text{shed}} \] Involuntarily load shedding of the \( d \)th demand under scenario \( \omega \) [MW]

Parameters:
\[ P_{d,(1)}^{B} \] Quantity bid of the \( d \)th demand [MW]
\[ P_{i,(1)}^{W} \] Quantity offer of the \( i \)th conventional unit, equal to its installed capacity [MW]
\[ P_{\omega,(1)}^{WE} \] Power forecast of wind producer under scenario \( \omega \) [MW]
\[ \lambda_{i}^{G} \] Offer price of the \( i \)th conventional unit, equal to its marginal cost
\[ \lambda_{i}^{U} \] Reserve-up offer price of the \( i \)th conventional unit
\[ \lambda_{i}^{D} \] Reserve-down offer price of the \( i \)th conventional unit
\[ \gamma_{\omega} \] Probability of scenario \( \omega \)
\[ R_{i}^{U} \] Reserve-up capacity of the \( i \)th conventional unit [MW]
\[ R_{i}^{D} \] Reserve-down capacity of the \( i \)th conventional unit [MW]
\[ V_{d}^{\text{shed}} \] Value of lost load for demand \( d \) [$/MWh]

The strategic quantity offering of the wind producer is modeled through a stochastic complementarity approach \([21], [24]\). We use a bi-level 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 two-stage market through minimizing the expected system cost. The UL objective function (1a) is constrained by both UL constraint (1b) and LL problem (2). Dual variables are indicated in objective function (1a) is constrained by both UL constraint (1b) and LL problem (2). Dual variables are indicated in objective function (1a) is constrained by both UL constraint (1b) and LL problem (2). Dual variables are indicated in objective function (1a) is constrained by both UL constraint (1b) and LL problem (2). Dual variables are indicated in objective function (1a) is constrained by both UL constraint (1b) and LL problem (2). Dual variables are indicated in objective function (1a) is constrained by both UL constraint (1b) and LL problem (2). Dual variables are indicated in objective function (1a) is constrained by both UL constraint (1b) and LL problem (2).

Maximize
\[
\mathcal{E}^{(1)} \left( \lambda^{DA,(1)} p_{WDA,(1)} + \sum_{\omega \in \Omega} \lambda_{\omega}^{RT,(1)}(p_{\omega}^{W,(1)} - p_{WDA,(1)} - p_{\omega}^{\text{spill},(1)}) \right)
\]
subject to
\[
p_{Wof,(1)} \geq 0
\]
where
\[
\lambda^{DA,(1)}, p_{WDA,(1)}, \lambda^{RT,(1)} \text{ and } p_{\omega}^{\text{spill},(1)} \forall \omega, \in
\]
arg minimize \( y^{(1)} \)
\[
C^{(1)} = \sum_{i \in I} \lambda_{i}^{G} p_{i,(1)}^{G} + \sum_{\omega \in \Omega} \gamma_{\omega} \left[ \sum_{i \in I} (\lambda_{i}^{U} r_{i,\omega}^{U,(1)} - \lambda_{i}^{D} r_{i,\omega}^{D,(1)}) \right] + \sum_{d \in D} V_{d}^{\text{shed}} p_{d,\omega}^{\text{shed}}
\]
subject to
\[
\sum_{d \in D} \sum_{i \in I} (p_{i,(1)}^{G} - p_{WDA,(1)} - p_{\omega}^{\text{spill},(1)}) = 0
\]
\[
0 \leq p_{i,(1)}^{G} \leq p_{G,(1)}^{i} ; \phi_{i,(1)}^{G} ; p_{i,(1)}^{U} \leq p_{U,(1)}^{i} ; \phi_{i,(1)}^{U} \forall i
\]
\[
0 \leq p_{WDA,(1)} \leq \frac{p_{WDA,(1)}}{p_{WDA,(1)}} ; \phi_{i,(1)}^{D} \forall \omega
\]
\[
\sum_{i \in I} (p_{i,(1)}^{D} - p_{i,(1)}^{U}) - \sum_{d \in D} p_{d,\omega}^{\text{shed}} - (P_{d,(1)}^{WDA} - p_{WDA,(1)} - p_{\omega}^{\text{spill},(1)}) = 0
\]
\[
\sum_{\omega \in \Omega} \gamma_{\omega} r_{d,\omega}^{L} \forall d, \forall \omega
\]
where \( Z \) variables of the LL problem. Furthermore, therefore convex, bi-level model (1)-(2) can be recast as quantity. Operational reserves are bounded by reserve capacity dual variable provides the probability-weighted RT market- power imbalances by operational reserve deployment, wind imposes the power balance in DA, whose dual variable, i.e., system cost including generation-side costs in DA and RT as The UL constraint (1b) imposes the wind power quantity offers The UL constraint (1b) imposes the wind power quantity offers

The UL objective function (1a), which maximizes the wind producer’s expected profit, consists of:

- The producer’s operation revenue in DA market, being the product of DA price (\( \lambda_{DA}^{(1)} \)) and scheduled quantity (\( p^{WDA,(1)} \)).
- The producer’s expected operation revenue/cost in RT market, being the product of the probability-weighted RT price (\( \lambda_{RT}^{(1)} \)) and wind power excess/deficit in real time, i.e., \( (P_{w}^{WDA}) - p^{WDA,(1)} - p_{w}^{(1)} \).

The UL constraint (1b) imposes the wind power quantity offers to be non-negative.

The UL 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) imposes the power balance in DA, whose dual variable, i.e., \( \lambda_{DA}^{(1)} \), provides the DA market-clearing price. Constraints (2c) and (2d) bind the DA schedule of conventional units and wind producer, respectively, based on their quantity offers. Constraint (2e) refers to power balance in RT that fixes the power imbalances by operational reserve deployment, wind power spillage and load shedding. Note that its corresponding dual variable provides the probability-weighted RT market-clearing price, i.e., \( \lambda_{RT}^{(1)} \). Constraint (2f) implies that wind power spillage should be equal to or lower than the wind power realization. Constraint (2g) restricts the load shedding quantity. Operational reserves are bounded by reserve capacity and production availability through (2h)-(2k).

Given that LL problem (2) is continuous, linear and therefore convex, bi-level 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 [21], [22] as given by (3) below:

\[
\text{Maximize } \Xi^{(1)} \quad \text{(3a)}
\]

subject to

(1b), (2b) and (2c)

\[ \lambda_{i} - \lambda_{DA}^{(1)} - g_{i}^{(1)} + \sum_{\omega} (\mu_{i,\omega}^{(1)} - m_{i,\omega}^{(1)}) = 0 \forall i \quad \text{(3e)} \]

\[ -\lambda_{DA}^{(1)} - g_{i}^{(1)} + \sum_{\omega} \lambda_{RT}^{(1)} = 0 \quad \text{(3d)} \]

\[ \gamma_{\omega} - \lambda_{w}^{RT}(i) - L_{i}^{U(1)} + L_{i}^{U(1)} + R_{i}^{(1)} = 0 \forall i, \omega \quad \text{(3f)} \]

\[ \gamma_{\omega} - V_{d}^{\text{shed}} - \lambda_{w}^{RT}(i) + \sum_{\omega} \gamma_{w}^{(1)} - \gamma_{w}^{(1)} = 0 \forall d, \omega \quad \text{(3g)} \]

\[ \lambda_{RT}^{(1)} + \sum_{\omega} \lambda_{w}^{RT}(i) - \sum_{\omega} \mu_{i,\omega}^{(1)} = 0 \forall \omega \quad \text{(3h)} \]

\[ 0 \leq \lambda_{w}^{RT}(i) \leq \varphi_{\omega}^{(1)} \geq 0 \forall i \quad \text{(3i)} \]

\[ 0 \leq \varphi_{\omega}^{(1)} \leq \varphi_{\omega}^{d,\omega} \geq 0 \forall d, \omega \quad \text{(3j)} \]

\[ 0 \leq \varphi_{\omega}^{(1)} \leq \gamma_{w}^{(1)} \geq 0 \forall \omega \quad \text{(3k)} \]

\[ 0 \leq \varphi_{\omega}^{d,\omega} \leq \sum_{\omega} \varphi_{\omega}^{d,\omega} \geq 0 \forall d, \omega \quad \text{(3l)} \]

\[ 0 \leq \varphi_{\omega}^{d,\omega} \leq \sum_{\omega} \varphi_{\omega}^{d,\omega} \geq 0 \forall d, \omega \quad \text{(3m)} \]

\[ 0 \leq \varphi_{\omega}^{(1)} \leq \gamma_{w}^{(1)} \geq 0 \forall \omega \quad \text{(3n)} \]

\[ 0 \leq \varphi_{\omega}^{d,\omega} \leq \sum_{\omega} \varphi_{\omega}^{d,\omega} \geq 0 \forall d, \omega \quad \text{(3o)} \]

\[ 0 \leq \varphi_{\omega}^{d,\omega} \leq \sum_{\omega} \varphi_{\omega}^{d,\omega} \geq 0 \forall d, \omega \quad \text{(3p)} \]

\[ 0 \leq \varphi_{\omega}^{d,\omega} \leq \sum_{\omega} \varphi_{\omega}^{d,\omega} \geq 0 \forall d, \omega \quad \text{(3q)} \]

\[ 0 \leq \varphi_{\omega}^{d,\omega} \leq \sum_{\omega} \varphi_{\omega}^{d,\omega} \geq 0 \forall d, \omega \quad \text{(3r)} \]

\[ 0 \leq \varphi_{\omega}^{d,\omega} \leq \sum_{\omega} \varphi_{\omega}^{d,\omega} \geq 0 \forall d, \omega \quad \text{(3s)} \]

\[ 0 \leq \varphi_{\omega}^{d,\omega} \leq \sum_{\omega} \varphi_{\omega}^{d,\omega} \geq 0 \forall d, \omega \quad \text{(3t)} \]

\[ 0 \leq \varphi_{\omega}^{d,\omega} \leq \sum_{\omega} \varphi_{\omega}^{d,\omega} \geq 0 \forall d, \omega \quad \text{(3u)} \]

\[ 0 \leq \varphi_{\omega}^{d,\omega} \leq \sum_{\omega} \varphi_{\omega}^{d,\omega} \geq 0 \forall d, \omega \quad \text{(3v)} \]

\[ \text{MPEC (3) is non-linear due to the following two sources of non-linearities:} \]

- The bi-linear terms \( \lambda_{DA}^{(1)} - \lambda_{RT}^{(1)} - m_{i,\omega}^{(1)} - \mu_{i,\omega}^{(1)} \) included in the objective function (3a).
- Complementarity conditions (3i)-(3v).

The bi-linear terms inside the objective function (3a) are linearized based on an approach without approximation, which is firstly proposed in [25]. Accordingly, we deploy the strong duality theorem [26] and mathematical expressions (3b)-(3h). Regarding complementarity conditions (3i)-(3v), they can be linearized using Big-M approach, but at the cost of introducing a set of auxiliary binary variables [27], [28]. Following these two linearization techniques, MPEC (3) is transformed into a mixed-integer linear programming (MILP) problem.

D. Step 2: Stochastic DA Market Clearing

In step 2, the market operator stochastically clears the DA market considering all wind power scenarios in RT [16–18], [29]. The aim of the market operator is to minimize the expected overall system cost in DA and RT. To this purpose, it solves stochastic two-stage programming problem (4). Note that the scenarios considered in (4) are those generated based on market operator’s forecast (indexed by \( s \)), which refers to the non-sharing analysis. In sharing analysis, such an index is replaced by \( h \) referring to shared scenarios.

The symbols used in (4) that have not already been defined in Step 1 are listed below. Note that superscript (2) refers to variables and parameters in Step 2. In addition, the quantity offer of the wind producer denoted by \( P^{WDA,(1)} \) is a parameter in this step, whose value is obtained from Step 1.
where $\Xi^{(2)} = \{p_i^{G; (2)} \forall i; r_i^{U; (2)} \forall i; r_i^{D; (2)} \forall i; l_{d; s}^{shed} \forall d, \forall s; p_{s}^{spill; (2)} \forall s; p^{WDA; (2)} \}$ is the set of primal variables. Objective function (4a) minimizes the expected overall system cost in DA and RT markets. In addition, constraints (4b)-(4k) are similar to constraints (2b)-(2k) in Step 1.

E. Step 3: RT Market Clearing (Out-of-Sample Simulation)

In this step, we fix the DA schedule of conventional units and wind producer to those obtained in Step 2. Then, RT market is cleared versus different wind power realizations, which are not necessarily the same with the scenarios considered in Steps 1 and 2. The RT market versus a particular wind power realization is given by deterministic optimization problem (5).

The new notation used in this subsection is given below. Note that symbols with superscript (3) refer to variables of Step 3, while those with superscript (2) correspond to parameters (DA schedules), whose values are obtained from Step 2.

\[
\begin{align*}
\Xi^{(3)} = \{ & p_i^{G; (3)} \forall i; r_i^{U; (3)} \forall i; r_i^{D; (3)} \forall i; l_{d; s}^{shed} \forall d, \forall s; p_{s}^{spill; (3)} \forall s; p^{WDA; (2)} \}.
\end{align*}
\]

subject to

\[
\sum_{i \in I} \lambda_i^G P_i^{G; (2)} + \sum_{s \in S} \pi_s \left[ \sum_{i \in I} (\lambda_i^U r_i^{U; (2)} - \lambda_i^D r_i^{D; (2)}) + \sum_{d \in D} l_{d; s}^{shed} \right] = \Xi^{(2)}
\]

where $\Xi^{(2)} = \{p_i^{G; (2)} \forall i; r_i^{U; (2)} \forall i; r_i^{D; (2)} \forall i; l_{d; s}^{shed} \forall d, \forall s; p_{s}^{spill; (2)} \forall s; p^{WDA; (2)} \}$ is the set of primal variables. Objective function (4a) minimizes the expected overall system cost in DA and RT markets. In addition, constraints (4b)-(4k) are similar to constraints (2b)-(2k) in Step 1.

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\end{align*}
\]

subject to

\[
\sum_{i \in I} \lambda_i^G P_i^{G; (2)} + \sum_{s \in S} \pi_s \left[ \sum_{i \in I} (\lambda_i^U r_i^{U; (2)} - \lambda_i^D r_i^{D; (2)}) + \sum_{d \in D} l_{d; s}^{shed} \right] = \Xi^{(2)}
\]

where $\Xi^{(2)} = \{p_i^{G; (2)} \forall i; r_i^{U; (2)} \forall i; r_i^{D; (2)} \forall i; l_{d; s}^{shed} \forall d, \forall s; p_{s}^{spill; (2)} \forall s; p^{WDA; (2)} \}$ is the set of primal variables. Objective function (4a) minimizes the expected overall system cost in DA and RT markets. In addition, constraints (4b)-(4k) are similar to constraints (2b)-(2k) in Step 1.
III. Case Study

A. Data

A single-hour case study based on the IEEE one-area reliability test system is considered [30]. For the sake of simplicity, conventional units are grouped by type and transmission network is not considered. Each conventional unit offers at a quantity identical to its installed capacity and at a price identical to its marginal cost as given in Table I. In addition to the conventional units, a single wind power producer is considered with the installed capacity of 1500 MW. The system load is 2850 MW, and its value of lost load is assumed to be $200/MWh.

In this study, a Beta distribution with shape parameters \((a_R, b_R)\) is considered. Then, 5000 samples are generated representing actual wind power realizations. These samples are in per-unit, i.e., wind production divided by installed wind capacity. Note that the number of samples is arbitrarily chosen to make an appropriate trade-off between accuracy and computational burden. These samples are used in Step 3 for the out-of-sample simulation. The wind producer’s and the market operator’s forecasts, to be used in Steps 1 and 2, are also modeled using a Beta distribution but with different shape parameters, i.e., \((a_W, b_W)\) and \((a_{MO}, b_{MO})\) respectively. The wind producer and the market operator generate 2000 scenarios each, and then they reduce them into three scenarios using a scenario reduction approach, e.g., the K-means method [31]. To this end, let us assume wind producer’s scenarios are \(\{\omega_1, \omega_2, \omega_3\}\) with their corresponding probabilities. In addition, market operator’s scenarios are \(\{s_1, s_2, s_3\}\) with their own corresponding probabilities. In the non-sharing analysis, wind producer solves Step 1 considering its own scenarios, and then market operator solves Step 2 based on its own different set of scenarios. However, they both use the same set of scenarios in the sharing analysis including all six scenarios, i.e., \(\{\omega_1, \omega_2, \omega_3, s_1, s_2, s_3\}\), in Steps 1 and 2. Note that the probability of each scenario in the sharing analysis is half of that in the non-sharing one.

In this case study, three different sets for Beta distribution shape parameters are examined as given in Table II, which yield different distribution shapes as depicted in Fig. 2. These three sets correspond to cases with high-mean, mid-mean and low-mean distributions, i.e., \(a>b\), \(a\approx b\), \(a<b\). We refer to those cases as Sets 1, 2 and 3, respectively. Based on the considered shape parameters representing actual realizations (5000 samples), the expected wind power production is 37%, 27% and 16% of the total system load for Set 1, Set 2 and Set 3, respectively.

\(B. \) Results: Non-sharing Analysis

In this subsection, we assume that the wind producer and the market operator don’t share their forecast distributions. The wind producer solves the mixed-integer form of MPEC (3) in Step 1 considering its own three scenarios and derives its most beneficial quantity offer as depicted in Fig. 3 by blue bars. Given producer’s quantity offer, market operator solves problem (4) in Step 2 to clear the DA market considering its own three scenarios, which are different than the wind producer’s ones. This step provides the DA wind schedule as depicted in Fig. 3 by green bars. Additionally, the expected wind power production, considering 5000 samples as potential realizations in Step 3, is illustrated by red bars.

According to the results obtained for Set 1, the wind producer forecasts a comparatively higher wind production with respect to the market operator. Therefore, the market operator schedules the wind producer at a quantity lower than the wind producer’s quantity offer. The expected actual wind power is in between.

Regarding Set 2, the market operator forecasts a comparatively higher production than the wind producer. However, the DA wind power schedule cannot exceed the producer’s quantity offer, therefore, the DA wind schedule is equal to the wind producer’s quantity offer. The expected wind realization in this case is higher than the scheduled wind power in DA market.

Finally in Set 3, the wind producer and the market operator forecast a comparatively low wind power generation, however, it is fully dispatched in the DA market. The expected wind realization in this case is slightly lower than the scheduled wind power in DA market.

\(C. \) Results: Sharing Analysis

In this subsection, we consider that the wind producer and the market operator share their wind power forecast distributions. Therefore, an identical scenario set including
In this paper, the value of sharing wind power forecasts is evaluated. This section numerically measures wind producer’s market power in sharing and non-sharing cases through a sensitivity analysis. To this end, we use the value obtained for the dual variable corresponding to the upper bound of constraint (4d) in Step 2. This value implies the sensitivity of system cost with respect to the wind producer’s strategic quantity offer. As given in Table VI, its absolute value in the non-sharing analysis is lower than that in the sharing one. More specifically, that value is zero for Sets 1 and 3 of the non-sharing analysis, while it is non-zero considering the sharing analysis. This implies that sharing forecasts with the market operator helps the wind producer to alter the market-clearing outcomes to its own benefit. Note that the negative value for such a dual variable means that system cost increases with the strategic quantity offers of the wind producer.

E. Sensitivity Analysis

As reported in the previous subsection, wind producer’s expected profit increases by sharing forecasts. A part of this profit increment happens due to the generation of a more qualified set of scenarios. Besides, it happens as the wind producer is able to behave more strategically with more information access. This section numerically measures wind producer’s market power in sharing and non-sharing cases through a sensitivity analysis. To this end, we use the value obtained for the dual variable corresponding to the upper bound of constraint (4d) in Step 2. This value implies the sensitivity of system cost with respect to the wind producer’s strategic quantity offer. As given in Table VI, its absolute value in the non-sharing analysis is lower than that in the sharing one. More specifically, that value is zero for Sets 1 and 3 of the non-sharing analysis, while it is non-zero considering the sharing analysis. This implies that sharing forecasts with the market operator helps the wind producer to alter the market-clearing outcomes to its own benefit. Note that the negative value for such a dual variable means that system cost increases with the strategic quantity offers of the wind producer.

IV. Conclusion

In this paper, the value of sharing wind power forecasts between a single wind power producer and the market operator is evaluated. This potential value is numerically evaluated in terms of the system cost. To this purpose, a three-step evaluation framework is proposed. At the first step, a stochastic bi-level optimization model is formulated, which allows the wind producer to derive its most beneficial quantity offer. At the second step, the market operator stochastically clears the DA market considering all potential wind power realizations in real time. At the last step, the RT market is deterministically cleared for a large number of wind power realizations constrained by fixed DA schedules. This framework is applied for two cases: (1) the wind producer and the market operator use different wind power scenarios (non-sharing analysis), and (2) the wind producer and the market operator share their wind power scenarios (sharing analysis). In addition, the impact of sharing wind power forecasts on strategic offering of the wind producer is analyzed using a relevant sensitivity analysis.
For a large case study, it is numerically concluded that sharing forecasts decreases the expected system cost while it increases the expected profit of the wind producer. However, the conventional units’ expected profit may decrease. The sensitivity analysis also shows that sharing forecasts may help the wind producer to alter the market-clearing outcomes to its own benefit (strategic behavior).

The investigation of the same problem for a case with multiple wind power producers, which forms an equilibrium problem with equilibrium constraints (EPEC) [32], is left for future research. Another EPEC problem can be considered for a case with strategic conventional producers. Finally, it is also relevant to analyze how sharing wind power forecasts changes the market equilibria.

REFERENCES


