Sharing Wind Power Forecasts in Electricity Markets: A Numerical Analysis

Lazaros Exizidis[a,*], S. Jalal Kazempour[b], Pierre Pinson[b], Zacharie de Greve[a], François Vallée[a]

[a] *Department of Electrical Engineering, University of Mons, Mons, 7000 Belgium*
[b] *Department of Electrical Engineering, Technical University of Denmark, Kgs. Lyngby, 2800 Denmark*

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 updated wind power forecast 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 the potential value of sharing forecasts 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.

Keywords: Wind power, forecast sharing, day-ahead, real-time, two-stage market clearing, out-of-sample simulation.

*Corresponding author
Email addresses: lazaros.exizidis@umons.ac.be (Lazaros Exizidis), seykaz@elektro.dtu.dk (S. Jalal Kazempour), ppin@elektro.dtu.dk (Pierre Pinson), zacharie.degreve@umons.ac.be (Zacharie de Greve), francois.vallee@umons.ac.be (François Vallée)

Nomenclature

Indices:

ω	Index for scenarios generated based on wind producer's forecast
s	Index for scenarios generated based on market operator's forecast
i	Index for conventional units
d	Index for demands

Sets:

Ω	Set of wind producer's scenarios
$\mathcal{I}$	Set of conventional units
$\mathcal{D}$	Set of demands
$\mathcal{S}$	Set of market operator's wind power scenarios

Parameters:

P_d^{D}	Quantity bid of demand d [MW]
P_i^{G}	Quantity offer of unit i [MW]
P^{act}	Actual wind power realization [MW]
P_s^{MO}	Wind power forecast of market operator under scenario s [MW]
P_ω^{W}	Power forecast of wind producer under scenario ω [MW]
λ_i^{G}	Offer price of unit i [$/MWh]
λ_i^{U}	Reserve-up offer price of unit i [$/MWh]
λ_i^{D}	Reserve-down offer price of unit i [$/MWh]
γ_ω	Probability of scenario ω
π_s	Probability of scenario s
R_i^{U}	Reserve-up capacity of unit i [MW]
R_i^{D}	Reserve-down capacity of unit i [MW]
V_d^{shed}	Value of lost load for demand d [$/MWh]

DA Variables:

$\lambda^{\mathrm{DA},(.)}$	DA market-clearing price [$/MWh]
$p_i^{\mathrm{G},(.)}$	DA dispatch of unit i [MW]
$p^{\mathrm{W},(.)}$	DA dispatch of wind producer [MW]
$p^{\mathrm{W,of},(.)}$	Quantity offer of wind producer [MW]

RT Variables:

$\lambda_{\omega}^{\mathrm{RT},(.)}$ Probability-weighted RT market-clearing price under scenario ω [$/MWh]

$p_{\omega}^{\mathrm{spill},(.)}$ Wind power spillage under scenario ω [MW]

$r_{i,\omega}^{\mathrm{U},(.)}$ Reserve-up deployed by unit i under scenario ω [MW]

$r_{i,\omega}^{\mathrm{D},(.)}$ Reserve-down deployed by unit i under scenario ω [MW]

$l_{d,\omega}^{\mathrm{shed},(.)}$ Involuntarily load shedding of demand d under scenario ω [MW]

Note that superscript (.) within variables refers to the corresponding step of the study (Steps 1, 2 or 3) and the definition of each RT variable with subscript s is similar to that with subscript ω, but under market operator's scenarios.

1. Introduction

Over 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 by the end of 2014 [1]. Germany is currently the leading country in terms of installed capacity with more than 39 GW, 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. In [3] the impact of spatially correlated wind production on market behaviors is assessed, while in [4] the market value of offshore wind on the electricity spot market in Germany is evaluated. A statistical analysis of a competitive day-ahead market coupled with correlated wind production and electric load is presented in [5]. Lastly, in [6] the effect of short-term forecasting accuracy of wind power on the offering strategy of wind producers is investigated. 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 [7] 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 [8, 9, 10]. This error leads to several operational challenges in electricity markets as addressed in [11, 12, 13, 14]. One potential solution to cope with those challenges is to add various operational flexible resources to the market such as peaking units and demand response providers [15]. The operational value of those resources is evaluated in [16, 17, 18].

In this paper, we address another potential solution for system functioning improvement, i.e., sharing wind power forecasts among different players, which may assist market players to build a more accurate wind power distribution than the one they individually forecast. Note that this sharing mechanism can improve the forecast of each player only if the shared forecasts are not fully correlated. This condition is consistent with the real-world electricity markets because the forecast of each market player is dependent not only on public numerical weather prediction (NWP) models, but also on the forecasting methodology of that player and its historical forecast error data. In case we assume that all players have the same beliefs about all technical characteristics of the system except the future wind power, sharing wind power forecasts allows to characterize the market competition as a game-theoretic model with complete information (instead of one with incomplete information).

In this paper, we consider a short-run electricity market with two sequential trading floors: day-ahead (DA) and real-time (RT) markets. The DA market is cleared based on all bids and offers, such as wind producers' offers. Given the fixed DA decisions, the market operator clears RT market based on updated wind power forecasts, which might be different than the wind producers' dispatch in DA market. Two different setups are generally available in the literature to manage wind power uncertainty within a sequential DA-RT framework: deterministic and stochastic. In the first one, the market operator clears DA market based on all submitted bids and offers (including wind producers' offers) and determines the DA schedules, while no other possibility for future wind power realization is considered. However, the market operator accommodates a number of market products, e.g., flexiramp [19], based on exogenous minimum requirements to provide operational flexibility against future wind power mismatch. In contrast, DA market is cleared stochastically in the second setup in which the market operator clears the DA market considering submitted bids and offers (including wind producers' offers) as well as a number of scenarios for future wind power realization [20, 21, 22, 23, 24, 25, 26]. In this paper, we use a stochastic market setup for two main reasons. Firstly, it results in more informed DA schedules than the deterministic one, and therefore, reduces the total expected system cost, given that wind scenarios represent accurately enough the actual realization [22]. Secondly, the nature of information sharing is stochastic, i.e., the deterministic setup avoids appropriately capturing different features of shared information. Under this stochastic setup, the mathematical problem for clearing DA market is formed as a stochastic two-stage programming problem [27], whose outcomes are scenario-independent DA schedules (here-and-now decisions) and scenario-dependent RT operations (wait-and-see decisions).

Under the context above, we consider a market in which the wind producer and the market operator independently forecast wind production in DA timescale. It is intuitively expected that sharing wind power forecasts among wind producers and 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 the considered market setup, one potential concern is that sharing wind power forecasts among wind producers and market operator may bring market power for wind producers to alter market-clearing outcomes to their own profits. In other words, each wind producer may behave more strategically if it has better knowledge on its stochastic production. To address such a concern, we use a game-theoretic complementarity approach [28, 29, 30] to model the strategic behavior of a wind producer with and without sharing forecasts. This requires solving a stochastic mathematical program with equilibrium constraints (MPEC) [31] to determine the optimal offering strategy of wind producer. The consideration of multiple wind producers yields a stochastic equilibrium problem with equilibrium constraints (EPEC), which is generally hard-to-solve. Pursuing simplicity and in order to make our findings more intuitive, we consider a single wind producer forming a stochastic MPEC [32]. However, information sharing analysis considering multiple wind producers is our future extension.

Another potential concern is that the analysis of this paper is subject to the realized wind power in RT. To address such a concern, we carry out an extensive out-of-sample simulation [33] considering a large number of different wind power realizations. This numerical analysis allows us to compare the expected system cost and the profit of each individual producer with and without sharing wind power forecasts.

Under this context, the contribution of this paper is fourfold:

- To propose a new potential alternative for reducing the social cost in electricity markets, which is based on information sharing among different agents. To the best of our knowledge, there is no relevant work in the technical literature addressing such an alternative.

- To propose a three-step evaluation framework that numerically assesses the value of sharing wind power forecasts between a wind producer and the market operator, which allows them to generate more qualified scenarios. This potential value is evaluated in terms of a reduction in expected system cost.

- To numerically analyze the impact of sharing wind power forecasts on potential strategic behavior of wind producer and on conventional producers' expected profits. The former is investigated through a sensitivity analysis.

- To carry out an extensive out-of-sample simulation that allows us to compare expected system cost and expected profit of different players with and without sharing wind power forecasts.

Note that the mathematical methodologies used in different steps of this study are already available in the literature, and therefore, the contributions of this work are not methodological. In turn, those available methods are used to propose information sharing among various actors, i.e., sharing wind power forecasts, as a potential solution for coping with wind uncertainty. Furthermore, the value of forecast sharing for the system is numerically assessed by a three-step evaluation framework and a sensitivity analysis. To the best of the authors' knowledge, there is no similar study in the current literature that investigates the effect of information sharing in electricity markets. The topic of this paper is of high interest to real-world electricity markets with significant penetration of renewable energy sources, e.g., the German, Danish and Irish markets.

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.

2. Evaluation Framework

2.1. Features and Assumptions

An imperfectly competitive electricity market is considered, in which the wind producer and conventional units may offer strategically [34, 35]. To avoid forming an EPEC, the strategic offering problem of wind producer is solved while assuming offer curve of rival conventional units as fixed parameters. These parameters are generally uncertain, which brings another source of uncertainty. In line with [36, 37, 38, 39], we exclude such an uncertainty. Therefore, we assume that the wind producer perfectly knows the offering strategy of its conventional rivals. Similarly to [35, 36, 38] 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. Unlike coal or gas-fired power plants, the operational cost of wind 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 [40]. As it is customary in the technical literature, e.g., [41, 42, 43, 44, 45], we assume that the wind production cost is zero. Finally, demand is assumed to be deterministic and inelastic to price, as in [46].

2.2. Proposed Three-Step Framework

The proposed three-step evaluation framework is schematically depicted in Fig. 1 and explained in detail as follows:

1. This step derives the offering strategy of wind producer through a game-theoretic complementarity model, whose objective is to maximize the wind producer's expected profit. Three offering options are available for the wind producer to exert its market power: i) strategic offering in terms of quantity, ii) strategic offering in terms of price, and iii) strategic offering in terms of both quantity and price. Note that the market impacts of all options are similar. In this paper, we consider the first option, i.e., the wind producer derives its strategic quantity offers. This allows the wind producer to withhold a part of its production. However, it offers

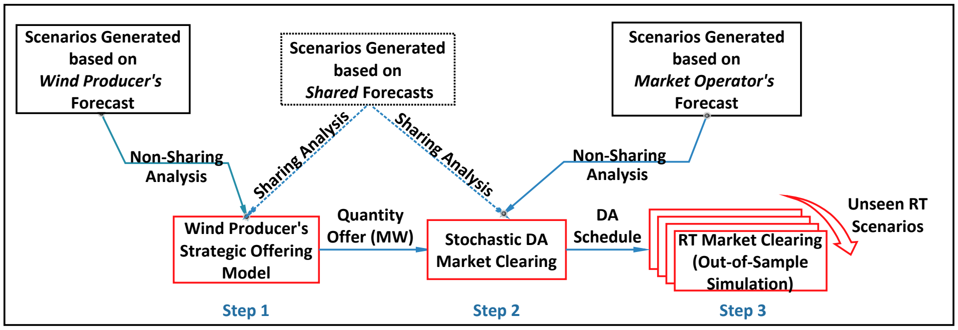

Figure 1: The proposed three-step evaluation framework: non-sharing and sharing analyses

its quantity at a non-strategic price, i.e., its marginal cost (zero). This offering setup for the wind producers is more consistent with the real-world markets since they usually offer at zero (or even negative [40]) price.

2. Given the quantity offer of the wind producer in Step 1, the market operator stochastically clears DA market considering foreseen wind power scenarios.

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 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.

2.3. Step 1: Offering Strategy of the Wind Producer

The strategic quantity offer of wind producer is derived in this step using a stochastic complementarity model, which is similar to one proposed in [36] and [37] but derives strategic quantity offers instead of price offers. To this end, we use bi-level model (1), whose upper-level problem, i.e., (1a)-(1b), maximizes wind producer's expected profit and derives strategic offers, and whose lower-level problem, i.e., (1c)-(1m), clears the market through minimizing the expected system cost. The upper-level objective function (1a) is constrained by both upper-level constraint (1b) and lower-level problem (1c)-(1m). Dual variables are indicated in each lower-level constraint after a colon. Note that in bi-level model (1), the wind producer's own scenarios ($\omega \in \Omega$) are considered (referring to non-sharing analysis), and therefore, variables and stochastic parameters are indexed by ω. In case of the sharing analysis, index ω needs to be replaced by a new one, e.g., index h, referring to the shared scenarios.

$$\underset{p^{\mathrm{W,of,(S1)}},\ \Xi^{\mathrm{LL,P}} \cup \Xi^{\mathrm{LL,D}}}{\text{Maximize}}$$

$$\lambda^{\mathrm{DA,(S1)}}\ p^{\mathrm{W,(S1)}} + \sum_{\omega \in \Omega} \lambda_{\omega}^{\mathrm{RT,(S1)}} \left(P_{\omega}^{\mathrm{W}} - p^{\mathrm{W,(S1)}} - p_{\omega}^{\mathrm{spill,(S1)}} \right) \tag{1a}$$

subject to

$$p^{\mathrm{W,of,(S1)}} \geq 0 \tag{1b}$$

$$\lambda^{\mathrm{DA,(S1)}}, p^{\mathrm{W,(S1)}}, \lambda_{\omega}^{\mathrm{RT,(S1)}}, p_{\omega}^{\mathrm{spill,(S1)}} \in \arg \underset{\Xi^{\mathrm{LL,P}}}{\text{minimize}} \Bigg\{$$

$$\sum_{i \in \mathcal{I}} \lambda_i^{\mathrm{G}}\ p_i^{\mathrm{G,(S1)}} + \sum_{\omega \in \Omega} \gamma_{\omega} \Bigg[\sum_{i \in \mathcal{I}} \left(\lambda_i^{\mathrm{U}}\ r_{i,\omega}^{\mathrm{U,(S1)}} - \lambda_i^{\mathrm{D}}\ r_{i,\omega}^{\mathrm{D,(S1)}} \right)$$

$$+ \sum_{d \in \mathcal{D}} V_d^{\mathrm{shed}}\ l_{d,\omega}^{\mathrm{shed,(S1)}} \Bigg] \tag{1c}$$

subject to

$$\sum_{d \in \mathcal{D}} P_d^{\mathrm{D}} - \sum_{i \in \mathcal{I}} p_i^{\mathrm{G,(S1)}} - p^{\mathrm{W,(S1)}} = 0 \ \ : \lambda^{\mathrm{DA,(S1)}} \tag{1d}$$

$$0 \leq p_i^{\mathrm{G,(S1)}} \leq P_i^{\mathrm{G}} \ \ : \underline{\phi_i}^{(\mathrm{S1})}, \overline{\phi_i}^{(\mathrm{S1})} \ \forall i \tag{1e}$$

$$0 \leq p^{\mathrm{W,(S1)}} \leq p^{\mathrm{W,of,(S1)}} \ \ : \underline{\sigma}^{(\mathrm{S1})}, \overline{\sigma}^{(\mathrm{S1})} \tag{1f}$$

$$\sum_{i \in \mathcal{I}} \left(r_{i,\omega}^{\mathrm{D,(S1)}} - r_{i,\omega}^{\mathrm{U,(S1)}} \right) - \sum_{d \in \mathcal{D}} l_{d,\omega}^{\mathrm{shed,(S1)}}$$

$$- \left(P_{\omega}^{\mathrm{W}} - p^{\mathrm{W,(S1)}} - p_{\omega}^{\mathrm{spill,(S1)}} \right) = 0 \ \ : \lambda_{\omega}^{\mathrm{RT,(S1)}} \ \forall \omega \tag{1g}$$

$$0 \leq p_{\omega}^{\mathrm{spill,(S1)}} \leq P_{\omega}^{\mathrm{W}} \ \ : \underline{\tau}_{\omega}^{(\mathrm{S1})}, \overline{\tau}_{\omega}^{(\mathrm{S1})} \ \forall \omega \tag{1h}$$

$$0 \leq l_{d,\omega}^{\mathrm{shed,(S1)}} \leq P_d^{\mathrm{D}} \ \ : \underline{\psi}_{d,\omega}^{(\mathrm{S1})}, \overline{\psi}_{d,\omega}^{(\mathrm{S1})} \ \forall d, \forall \omega \tag{1i}$$

$$0 \leq r_{i,\omega}^{\mathrm{D,(S1)}} \leq R_i^{\mathrm{D}} \ \ : \underline{\mu}_{i,\omega}^{\mathrm{D,(S1)}}, \overline{\mu}_{i,\omega}^{\mathrm{D,(S1)}} \ \forall i, \forall \omega \tag{1j}$$

$$0 \leq r_{i,\omega}^{\mathrm{U,(S1)}} \leq R_i^{\mathrm{U}} \ \ : \underline{\mu}_{i,\omega}^{\mathrm{U,(S1)}}, \overline{\mu}_{i,\omega}^{\mathrm{U,(S1)}} \ \forall i, \forall \omega \tag{1k}$$

$$r_{i,\omega}^{\mathrm{U,(S1)}} \leq \left(P_i^{\mathrm{G}} - p_i^{\mathrm{G,(S1)}} \right) \ \ : \overline{\mu}_{i,\omega}^{(\mathrm{S1})} \ \forall i, \forall \omega \tag{1l}$$

$$r_{i,\omega}^{\mathrm{D,(S1)}} \leq p_i^{\mathrm{G,(S1)}} \ \ : \underline{\mu}_{i,\omega}^{(\mathrm{S1})} \ \forall i, \forall \omega \Bigg\} \tag{1m}$$

where $\Xi^{\mathrm{LL,P}} = \{p_i^{\mathrm{G,(S1)}}, p^{\mathrm{W,(S1)}}, r_{i,\omega}^{\mathrm{U,(S1)}}, r_{i,\omega}^{\mathrm{D,(S1)}}, l_{d,\omega}^{\mathrm{shed,(S1)}}, p_\omega^{\mathrm{spill,(S1)}}\}$ is set of primal variables of lower-level problem (1c)-(1m). Furthermore, $\Xi^{\mathrm{LL,D}} = \{\underline{\phi_i}^{\mathrm{(S1)}}, \overline{\phi_i}^{\mathrm{(S1)}}, \underline{\sigma}^{\mathrm{(S1)}}, \overline{\sigma}^{\mathrm{(S1)}}, \lambda^{\mathrm{DA,(S1)}}, \underline{\tau}_\omega^{\mathrm{(S1)}}, \overline{\tau}_\omega^{\mathrm{(S1)}}, \lambda_\omega^{\mathrm{RT,(S1)}}, \underline{\psi}_{d,\omega}^{\mathrm{(S1)}}, \overline{\psi}_{d,\omega}^{\mathrm{(S1)}}, \underline{\mu}_{i,\omega}^{\mathrm{D,(S1)}}, \overline{\mu}_{i,\omega}^{\mathrm{D,(S1)}}, \underline{\mu}_{i,\omega}^{\mathrm{U,(S1)}}, \overline{\mu}_{i,\omega}^{\mathrm{U,(S1)}}, \overline{\mu}_{i,\omega}^{\mathrm{(S1)}}, \underline{\mu}_{i,\omega}^{\mathrm{(S1)}}\}$ is set of dual variables of the lower-level problem. Finally, the primal variables of the upper-level problem (1a)-(1b) are $p^{\mathrm{W,of,(S1)}}$ as well as all members of variable sets $\Xi^{\mathrm{LL,P}}$ and $\Xi^{\mathrm{LL,D}}$.

The upper-level objective function (1a) maximizes the wind producer's expected profit and includes:

- Wind producer's profit in DA market, being the product of DA market-clearing price, i.e., $\lambda^{\mathrm{DA,(S1)}}$, and scheduled quantity, i.e., $p^{\mathrm{W,(S1)}}$.
- Wind producer's expected profit/cost in RT market, being the product of the probability-weighted RT market-clearing price, i.e., $\lambda_\omega^{\mathrm{RT,(S1)}}$, and wind power excess/deficit in RT, i.e., $P_\omega^{\mathrm{W}} - p^{\mathrm{W,(S1)}} - p_\omega^{\mathrm{spill,(S1)}}$.

The upper-level constraint (1b) imposes the strategic quantity offer of wind producer, i.e., $p^{\mathrm{W,of,(S1)}}$, to be non-negative.

The lower-level objective function (1c) minimizes the expected system cost including generation-side costs in DA and RT as well as load shedding costs in RT. The lower-level constraint (1d) represents the power balance in DA, whose dual variable, i.e., $\lambda^{\mathrm{DA,(S1)}}$, provides the DA market-clearing price. Constraints (1e) and (1f) bind the DA schedule of conventional units and wind producer, respectively, based on their quantity offers. Constraint (1g) refers to power balance in RT that adjusts the energy imbalance 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., $\lambda_\omega^{\mathrm{RT,(S1)}}$. Constraint (1h) implies that wind power spillage should be equal to or lower than the wind power realization. Constraint (1i) restricts the load shedding quantity. Operational reserves in RT are bounded by reserve quantity offers and DA dispatch through (1j)-(1m).

Note that lower-level problem (1c)-(1m) is continuous, linear, and therefore convex. This allows bi-level model (1) to be recast as a single-level MPEC through replacing lower-level problem (1c)-(1m) by its Karush-Kuhn-Tucker (KKT) optimality conditions [28]. The resulting MPEC can be then transformed into a mixed-integer linear programming (MILP) problem through linearization techniques described in [47].

2.4. Step 2: Stochastic DA Market Clearing

In this step, the market operator clears stochastically the DA market considering all foreseen wind power scenarios. 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 (2). Note that the scenarios considered in (2) are those generated based on market operator's forecast (indexed by s), which refer to the non-sharing analysis. In sharing analysis, this index is replaced by h referring to the shared scenarios. Note also that the quantity offer of wind producer denoted by $P^{\mathrm{W,of,(S1)}}$ is a parameter in step 2, whose value is obtained from Step 1.

$$\underset{p_i^{\mathrm{G,(S2)}},p^{\mathrm{W,(S2)}},r_{i,s}^{\mathrm{U,(S2)}},r_{i,s}^{\mathrm{D,(S2)}},l_{d,s}^{\mathrm{shed,(S2)}},p_s^{\mathrm{spill,(S2)}}}{\text{Minimize}}$$

$$\sum_{i\in\mathcal{I}}\lambda_i^{\mathrm{G}}\ p_i^{\mathrm{G,(S2)}}+\sum_{s\in\mathcal{S}}\pi_s\Bigg[\sum_{i\in\mathcal{I}}\left(\lambda_i^{\mathrm{U}}\ r_{i,s}^{\mathrm{U,(S2)}}-\lambda_i^{\mathrm{D}}\ r_{i,s}^{\mathrm{D,(S2)}}\right)$$
$$+\sum_{d\in\mathcal{D}}V_d^{\mathrm{shed}}\ l_{d,s}^{\mathrm{shed,(S2)}}\Bigg] \tag{2a}$$

subject to

$$\sum_{d\in\mathcal{D}}P_d^{\mathrm{D}}-\sum_{i\in\mathcal{I}}p_i^{\mathrm{G,(S2)}}-p^{\mathrm{W,(S2)}}=0 \tag{2b}$$

$$0\le p_i^{\mathrm{G,(S2)}}\le P_i^{\mathrm{G}}\ \forall i \tag{2c}$$

$$0\le p^{\mathrm{W,(S2)}}\le P^{\mathrm{W,of,(S1)}} \tag{2d}$$

$$\sum_{i\in\mathcal{I}}\left(r_{i,s}^{\mathrm{D,(S2)}}-r_{i,s}^{\mathrm{U,(S2)}}\right)-\sum_{d\in\mathcal{D}}l_{d,s}^{\mathrm{shed,(S2)}}$$
$$-\left(P_s^{\mathrm{MO}}-p^{\mathrm{W,(S2)}}-p_s^{\mathrm{spill,(S2)}}\right)=0\ \forall s \tag{2e}$$

$$0\le p_s^{\mathrm{spill,(S2)}}\le P_s^{\mathrm{MO}}\ \forall s \tag{2f}$$

$$0\le l_{d,s}^{\mathrm{shed,(S2)}}\le P_d^{\mathrm{D}}\ \forall d,\forall s \tag{2g}$$

$$0\le r_{i,s}^{\mathrm{D,(S2)}}\le R_i^{\mathrm{D}}\ \forall i,\forall s \tag{2h}$$

$$0\le r_{i,s}^{\mathrm{U,(S2)}}\le R_i^{\mathrm{U}}\ \forall i,\forall s \tag{2i}$$

$$r_{i,s}^{\mathrm{U,(S2)}}\le\left(P_i^{\mathrm{G}}-p_i^{\mathrm{G,(S2)}}\right)\ \forall i,\forall s \tag{2j}$$

$$r_{i,s}^{\mathrm{D,(S2)}}\le p_i^{\mathrm{G,(S2)}}\ \forall i,\forall s. \tag{2k}$$

Objective function (2a) minimizes the expected overall system cost in DA and RT markets. In addition, constraints (2b)-(2k) are similar to constraints (1d)-(1m) in Step 1.

2.5. 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 (3). Note that symbols with superscript (S2) correspond to parameters (DA schedules), whose values are obtained from Step 2.

$$\underset{r_i^{\mathrm{U},(\mathrm{S3})}, r_i^{\mathrm{D},(\mathrm{S3})}, l_d^{\mathrm{shed},(\mathrm{S3})}, p^{\mathrm{spill},(\mathrm{S3})}}{\text{Minimize}}$$

$$\left\{ \sum_{i \in \mathcal{I}} \left(\lambda_i^{\mathrm{U}} \ r_i^{\mathrm{U},(\mathrm{S3})} - \lambda_i^{\mathrm{D}} \ r_i^{\mathrm{D},(\mathrm{S3})} \right) + \sum_{d \in \mathcal{D}} V_d^{\mathrm{shed}} \ l_d^{\mathrm{shed},(\mathrm{S3})} \right\} \tag{3a}$$

subject to

$$\sum_{i \in \mathcal{I}} \left(r_i^{\mathrm{D},(\mathrm{S3})} - r_i^{\mathrm{U},(\mathrm{S3})} \right) - \sum_{d \in \mathcal{D}} l_d^{\mathrm{shed},(\mathrm{S3})}$$

$$- \left(P^{\mathrm{act}} - P^{\mathrm{W},(\mathrm{S2})} - p^{\mathrm{spill},(\mathrm{S3})} \right) = 0 \tag{3b}$$

$$0 \leq p^{\mathrm{spill},(\mathrm{S3})} \leq P^{\mathrm{act}} \tag{3c}$$

$$0 \leq l_d^{\mathrm{shed},(\mathrm{S3})} \leq P_d^{\mathrm{D}} \ \forall d \tag{3d}$$

$$0 \leq r_i^{\mathrm{D},(\mathrm{S3})} \leq R_i^{\mathrm{D}} \ \forall i \tag{3e}$$

$$0 \leq r_i^{\mathrm{U},(\mathrm{S3})} \leq R_i^{\mathrm{U}} \ \forall i \tag{3f}$$

$$r_i^{\mathrm{U},(\mathrm{S3})} \leq \left(P_i^{\mathrm{G}} - P_i^{\mathrm{G},(\mathrm{S2})} \right) \ \forall i \tag{3g}$$

$$r_i^{\mathrm{D},(\mathrm{S3})} \leq P_i^{\mathrm{G},(\mathrm{S2})} \ \forall i. \tag{3h}$$

Objective function (3a) minimizes the imbalance cost incurred by operational reserve deployment and/or involuntarily load shedding. In addition, constraints (3b)-(3h) are similar to constraints (1g)-(1m) in Step 1.

3. Case Study

3.1. Data

A case-study based on the IEEE one-area reliability test system [48] is considered, in which conventional units are grouped by type and price. Each conventional unit offers at a quantity identical to its installed capacity and at a price given in Table 1. 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.

Table 1: 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

There are various scenario generation techniques suggested in the literature such as [49, 50, 51, 52, 53]. In this study, a Beta distribution with shape parameters $(a^{\mathrm{R}}, b^{\mathrm{R}})$ is considered [24]. Then, 5000 samples are generated representing potential 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 an extensive out-of-sample simulation. The wind producer's and the market operator's forecasts are used in Steps 1 and 2, and modeled using a Beta distribution but with different shape parameters, i.e., $(a^{\mathrm{W}}, b^{\mathrm{W}})$ and $(a^{\mathrm{MO}}, b^{\mathrm{MO}})$, 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 [54]. This provides wind producer's scenarios denoted as ω_1, ω_2 and ω_3 with their corresponding probabilities. Similarly, the market operator's scenarios are generated denoted as s_1, s_2 and s_3 with different 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 the half of the non-sharing one.

Pursuing generality, three different sets for the parameters of Beta distribution are examined in this case study as given in Table 2, which yield different distribution shapes. This way, we investigate the impact of forecast distributions on the results of non-sharing and sharing analyses. These sets are selected to represent the three cases with the most characteristic differences in the distribution shapes, i.e., cases with high-mean, mid-mean and low-mean distributions. These three sets correspond to shape parameters $a > b$, $a \simeq b$ and $a < b$ respectively. We refer to those cases as Sets 1, 2 and 3, respectively. Note that in this study, we assume that forecasts of wind producer and market operator have different distributions but they still predict the same shape of distribution, i.e., high-mean, mid-mean or low-mean. For clarity, the distribution shapes of actual wind power realization are illustrated in Fig. 2 considering values of a^{R} and b^{R} across different sets. 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.

Table 2: Shape Parameters of Beta Distributions

Shape Parameters	Set 1 $a > b$	Set 2 $a \simeq b$	Set 3 $a < b$
$(a^{\mathrm{R}}, b^{\mathrm{R}})$	(3.78,1.62)	(5.37,5.37)	(1.89,4.48)
$(a^{\mathrm{MO}}, b^{\mathrm{MO}})$	(3.58,2.02)	(5.17,5.77)	(1.69,4.88)
$(a^{\mathrm{W}}, b^{\mathrm{W}})$	(3.98,1.22)	(5.57,4.97)	(2.09,4.08)

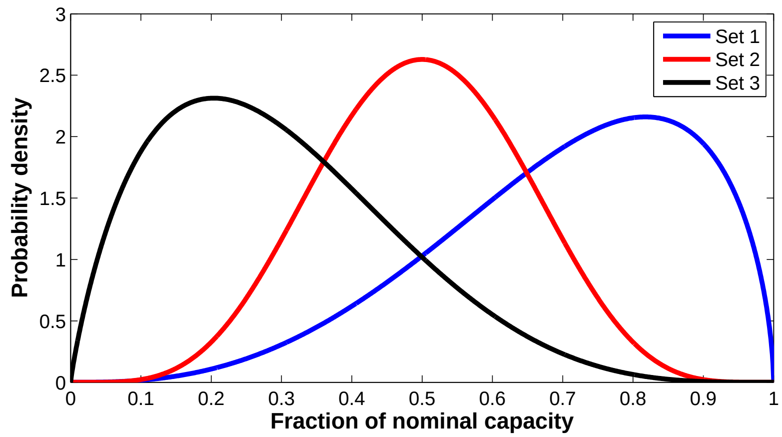

Figure 2: Actual wind power distribution considering Set 1 ($a^{\mathrm{R}} > b^{\mathrm{R}}$), Set 2 ($a^{\mathrm{R}} = b^{\mathrm{R}}$) and Set 3 ($a^{\mathrm{R}} < b^{\mathrm{R}}$)

In the rest of this section, Subsections 3.2 and 3.3 provide results for non-sharing and sharing analyses, respectively, considering different sets of wind power scenarios. In addition, Subsections 3.4 and 3.5 compare the results obtained from non-sharing and sharing analyses through an out-of-sample simulation and a sensitivity-based approach.

3.2. Results: Non-sharing Analysis

In this subsection, we assume that the wind producer and the market operator do not share their forecast distributions. The wind producer solves bi-level model (1) 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 (2) in Step 2 to clear DA market considering its own three scenarios, which are different than the wind producer's ones. This step provides the DA wind power dispatch 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

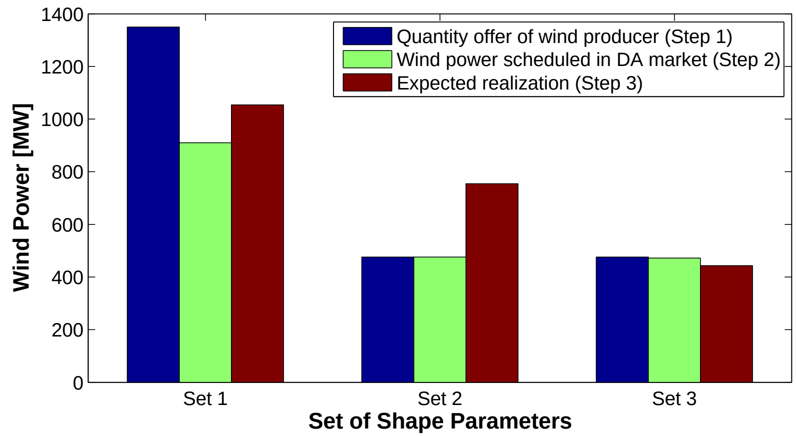

Figure 3: Non-sharing analysis: wind producer's quantity offer to DA market (Step 1), scheduled wind power in DA market (Step 2), and expected wind power realization in RT (Step 3)

DA market. The expected wind realization in this case is slightly lower than the scheduled wind power in DA market.

3.3. 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 six scenarios is considered within both Steps 1 and 2. Fig. 4 depicts the wind quantity offer (Step 1), the scheduled wind power in DA (Step 2) and the expected wind power realization (Step 3) obtained from the sharing analysis. In this analysis, the producer's quantity offer and the scheduled DA wind power are equal in each set since the wind producer and the market operator have the same beliefs on wind power production. As expected, the optimization models in Steps 1 and 2 yield the same results in the sharing analysis, because they are solved considering the same set of scenarios. This verifies the well-functioning of the mathematical models used in Steps 1 and 2.

3.4. Out-of-Sample Simulation Considering 5000 Samples

In this subsection, we clear the RT market in Step 3 for 5000 samples representing different wind power realizations, while DA decisions are fixed to those obtained from Step 2. Then, we compute the *actual* system cost that consists of the system cost in DA obtained from Step 2 plus the expected system cost in RT obtained from Step 3. As it is given in Table 3, the actual system cost in the sharing analysis is comparatively lower than (in case of Set 1) or equal to (in case of Sets 2 and 3) that in the non-sharing analysis. The reason is that sharing forecasts between the wind producer and the market operator can

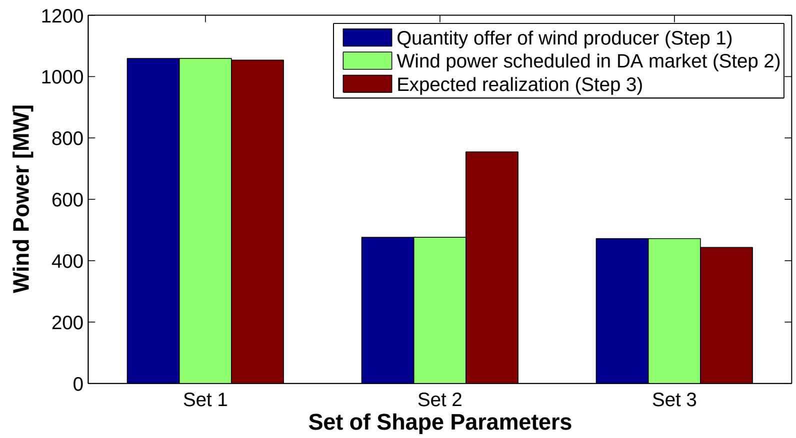

Figure 4: Sharing analysis: wind producer's quantity offer to DA market (Step 1), scheduled wind power in DA market (Step 2), and expected wind power realization in RT (Step 3).

Table 3: Actual System Cost [$]

Analysis	Set 1	Set 2	Set 3
Non-Sharing	24026	32845	32970
Sharing	20982	32845	32970

lead to the generation of more qualified scenarios in DA market. This numerically concludes that sharing forecasts can potentially reduce the system cost in systems with high wind power penetration.

Moreover, the DA and the expected RT market-clearing prices in both sharing and non-sharing analyses are reported in Tables 4 and 5. Note that the DA market-clearing price is derived from Step 2, whereas the expected RT market-clearing price is derived in Step 3 considering 5000 wind generation samples. The results of Table 4 imply that the DA market-clearing price for Set 2 increases in the sharing analysis, which consequently results in increased profits for all producers. The wind producer in this case exercises its market power in order to increase market prices and the rest of producers also benefit from increased prices.

In addition to the impact of sharing forecasts on actual system cost and market-clearing prices as social measures, its impact on different players' profit needs to be investigated. The expected profit of each player includes its profit in DA market (Step 2) plus its expected profit/cost in RT market (Step 3). Table 6 gives the wind producers' expected profit for the three different sets, while Table 7 presents the expected profit of each conventional unit. According to the results reported in Table 6, the wind producer benefits from sharing forecasts as its profit increases in the first two sets while it remains unchanged in Set 3. These results numerically reveal that sharing forecasts is beneficial for the wind

Table 4: Day-Ahead Price in different sets [$/MWh]

Analysis	Set 1	Set 2	Set 3
Non-Sharing	20.56	20.56	30.12
Sharing	20.56	30.12	30.12

Table 5: Expected Real-Time Price in different sets [$/MWh]

Analysis	Set 1	Set 2	Set 3
Non-Sharing	13.68	10.23	25.99
Sharing	18.86	10.23	25.99

producer due to finding better knowledge on its future stochastic production. Besides, information sharing brings more market power to wind producer to alter the market-clearing outcomes to its own benefit. More specifically, the wind power producer has a high level of production in Set 1 and benefits from having better knowledge of its expected generation. In Set 2, the expected wind power production is comparatively lower than that in Set 1, however, the wind producer withholds a part of its generation to increase the market-clearing prices and to gain more profit. Finally, Set 3 refers to a case with a low level of wind generation, in which the forecast sharing does not affect the market clearing outcomes. Further discussion on wind producer's profit is provided in the next subsection.

Unlike the wind producer, the conventional units may lose or may gain profit if the market operator and the wind producer share their forecasts. In Set 1, producers G1, G2 and G3 gain higher profits in the sharing analysis due to increased expected RT price (Table 5). In contrast, producers G5, G6 and G7 lose profit because their production levels are decreased. In both analyses, producer G4 is fully dispatched in DA market while the clearing price of that market is identical. Therefore, its profit does not change. In Set 2, the profits of most conventional producers increase because the DA price is significantly higher in the sharing analysis (Table 4). Results corresponding to Set 3 are identical in both analyses since the power schedule of units and market-clearing prices do not change.

Table 6: Expected Profit of The Wind Producer [$]

Analysis	Set 1	Set 2	Set 3
Non-Sharing	18107	10920	10223
Sharing	18937	15471	10223

Table 7: Expected Profit of The Conventional Units [$]

Unit	Analysis	Set 1	Set 2	Set 3
G1	Non-Sharing	0.5	0	9
	Sharing	50.5	0	9
G2	Non-Sharing	9.8	11	299.2
	Sharing	74.2	11	299.2
G3	Non-Sharing	0	0	0
	Sharing	7.2	0	0
G4	Non-Sharing	4668	4676	7538
	Sharing	4668	7544	7538
G5	Non-Sharing	1059	1231	5487
	Sharing	941.2	5762	5487
G6	Non-Sharing	717.3	830.52	7857
	Sharing	574.22	8478	7857
G7	Non-Sharing	10470	10505	18089
	Sharing	10425	18153	18089

3.5. Sensitivity Analysis

As reported in the previous subsection, the wind producer's expected profit may increase 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 dual variable corresponding to the upper bound of constraint (2d) 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 8, its absolute value in the non-sharing analysis is lower than in the sharing analysis. 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 reveals that sharing forecasts with market operator increases the ability of wind producer to exert market power. Note that the negative value for this dual variable means that system cost in DA market (Step 2) increases with the strategic behaviour of wind producer. However, recall that the actual system cost, i.e., the system cost in DA (obtained from Step 2) plus the expected system cost in RT (obtained from Step 3), can potentially decrease with information sharing as it has been already reported in Table 3. This reduction of total actual cost in sharing cases happens because less balancing sources are needed in RT.

Table 8: Value of Sensitivity Factor: Dual Variable Corresponding to the Upper Bound of Constraint (2d) in Step 2 [$/MWh]

Analysis	Set 1	Set 2	Set 3
Non-Sharing	0	-12.498	0
Sharing	-1.786	-22.909	-2.26

4. Conclusion

In this paper, the value of sharing wind power forecasts between a single wind power producer and a market operator is analyzed. This potential value is numerically evaluated in terms of system cost. To this purpose, a three-step evaluation framework is proposed. In the first step, a stochastic bi-level optimization model is formulated, which allows the wind producer to derive its most beneficial quantity offer. In the second step, the market operator clears stochastically the DA market considering all foreseen wind power realizations in real time. In the last step, the RT market is cleared deterministically for a large number of wind power realizations constrained by fixed DA schedules. This framework is applied for two cases: (i) the wind producer and the market operator use different wind power scenarios (non-sharing analysis), and (ii) 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 wind producer is analyzed using a relevant sensitivity analysis.

For a large case study, it is numerically concluded that sharing forecasts may decrease the expected system cost while it may increase the expected profit of wind producer. However, the expected profit of conventional producers is subject to the strategic behavior of wind producer and the quality of shared scenarios. On the one hand, wind producer may exert more market power, having access to more information. This will lead to higher market-clearing prices and, thus, higher profits for all producers. On the other hand, profits may decrease since sharing information can reduce the need for balancing resources in the RT stage. 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 consideration of multiple wind producers yields a stochastic equilibrium problem with equilibrium constraints (EPEC) [35, 55] and is left for future research. In addition, it is relevant to analyze how sharing wind power forecasts affects the market equilibria.

Acknowledgments

The work of L. Exizidis was partly supported by the public service of Wallonia-Department of Energy and Sustainable Building, within the framework of the GREDOR project, and partly by "Fonds National de La Recherche Scientifique (FNRS)". S. J. Kazempour and P. Pinson are partly supported by the Danish

Strategic Council for Strategic Research through the projects of PROAIN (no. 3045-00012B/DSF) and 5s - Future Electricity Markets (no. 12-132636/DSF).

References

[1] I. Pineda, J. Wilkes, Wind in power, Tech. rep., European Wind Energy Association (2015).

[2] Annual report 2014, Tech. rep., Energinet.dk (2014).

[3] M. Rahimiyan, A statistical cognitive model to assess impact of spatially correlated wind production on market behaviors, Applied Energy 122 (2014) pp. 62 – 72.

[4] N. Ederer, The market value and impact of offshore wind on the electricity spot market: Evidence from Germany, Applied Energy 154 (2015) pp. 805 – 814.

[5] R. Arjmand, M. Rahimiyan, Statistical analysis of a competitive day-ahead market coupled with correlated wind production and electric load, Applied Energy 161 (2016) pp. 153 – 167.

[6] G. Li, J. Shi, Agent-based modeling for trading wind power with uncertainty in the day-ahead wholesale electricity markets of single-sided auctions, Applied Energy 99 (2012) pp. 13 – 22.

[7] G. Giebel, R. Brownsword, G. Kariniotakis, M. Denhard, C. Draxl, The state-of-the-art in short-term prediction of wind power: A literature overview, Tech. rep. (2011).

[8] B. M. Hodge, M. Milligan, Wind power forecasting error distributions over multiple timescales, IEEE Power and Energy Society General Meeting (2011) pp. 1–8.

[9] E. Ela, M. O'Malley, Studying the variability and uncertainty impacts of variable generation at multiple timescales, IEEE Trans. Power Syst. 27 (3) (2012) pp. 1324–1333.

[10] H. Bludszuweit, J. A. Dominguez-Navarro, A. Llombart, Statistical analysis of wind power forecast error, IEEE Trans. Power Syst. 23 (3) (2008) pp. 983–991.

[11] S. Tewari, C. J. Geyer, N. Mohan, A statistical model for wind power forecast error and its application to the estimation of penalties in liberalized markets, IEEE Trans. Power Syst. 26 (4) (2011) pp. 2031–2039.

[12] P. Pinson, Wind energy: Forecasting challenges for its operational management, Statistical Science 28 (4) (2013) pp. 564–585.

[13] T. Jonsson, P. Pinson, H. Madsen, On the market impact of wind energy forecasts, Energy Economics 32 (2) (2010) pp. 313–320.

[14] A. Fabbri, T. G. S. Roman, J. R. Abbad, V. H. M. Quezada, Assessment of the cost associated with wind generation prediction errors in a liberalized electricity market, IEEE Trans. Power Syst. 20 (3) (2005) pp. 1440–1446.

[15] C. De Jonghe, B. F. Hobbs, R. Belmans, Value of price responsive load for wind integration in unit commitment, IEEE Trans. Power Syst. 29 (2) (2014) pp. 675–685.

[16] J. Zhao, T. Zheng, E. Litvinov, A unified framework for defining and measuring flexibility in power system, IEEE Trans. Power Syst. 31 (1) (2016) pp. 339–347.

[17] E. Lannoye, D. Flynn, M. O'Malley, Evaluation of power system flexibility, IEEE Trans. Power Syst. 27 (2) (2012) pp. 922–931.

[18] J. Ma, V. Silva, R. Belhomme, D. S. Kirschen, L. F. Ochoa, Evaluating and planning flexibility in sustainable power systems, IEEE Transactions on Sustainable Energy 4 (1) (2013) pp. 200–209.

[19] B. Wang, B. F. Hobbs, Real-time markets for flexiramp: A stochastic unit commitment-based analysis, IEEE Trans. Power Syst. 31 (2) (2016) pp. 846–860.

[20] S. Wong, J. D. Fuller, Pricing energy and reserves using stochastic optimization in an alternative electricity market, IEEE Trans. Power Syst. 22 (2) (2007) pp. 631–638.

[21] G. Pritchard, G. Zakeri, A. Philpott, A single-settlement, energy-only electric power market for unpredictable and intermittent participants, Oper. Res. 58 (4-part-2) (2010) pp. 1210–1219.

[22] J. M. Morales, A. J. Conejo, K. Liu, J. Zhong, Pricing electricity in pools with wind producers, IEEE Trans. Power Syst. 27 (3) (2012) pp. 1366–1376.

[23] S. Martin, Y. Smeers, J. A. Aguado, A stochastic two settlement equilibrium model for electricity markets with wind generation, IEEE Trans. Power Syst. 30 (1) (2015) pp. 233–245.

[24] J. M. Morales, M. Zugno, S. Pineda, P. Pinson, Electricity market clearing with improved scheduling of stochastic production, Eur. J. Oper. Res. 235 (3) (2014) pp. 765–774.

[25] Y. Zhang, G. B. Giannakis, Distributed stochastic market clearing with high-penetration wind power, IEEE Trans. Power Syst. 31 (2) (2016) pp. 895–906.

[26] V. Zavala, M. Anitescu, J. Birge, A stochastic electricity market clearing formulation with consistent pricing properties, Oper. Res., working paper. URL http://www.mcs.anl.gov/ anitescu/PUBLICATIONS/2014/zavala-stochpricing-2014.pdf.

[27] A. J. Conejo, M. Carrión, J. M. Morales, Decision Making Under Uncertainty in Electricity Markets, International Series in Operations Research & Management Science. New York, NY, USA: Springer, 2010.

[28] S. A. Gabriel, A. J. Conejo, J. D. Fuller, B. F. Hobbs, C. Ruiz, Complementarity Modeling in Energy Markets, International Series in Operations Research & Management Science. New York, NY, USA: Springer, 2012.

[29] L. Baringo, A. J. Conejo, Wind power investment within a market environment, Applied Energy 88 (9) (2011) pp. 3239–3247.

[30] N. Mahmoudi, T. K. Saha, M. Eghbal, Modelling demand response aggregator behavior in wind power offering strategies, Applied Energy 133 (2014) pp. 347 – 355.

[31] Z. Q. Luo, J. S. Pang, D. Ralph, Mathematical Programs with Equilibrium Constraints, Cambridge University Press, 1996.

[32] S. A. Gabriel, F. U. Leuthold, Solving discretely-constrained MPEC problems with applications in electric power markets, Energy Economics 32 (1) (2010) pp. 3 – 14.

[33] M. Rahimiyan, J. M. Morales, A. J. Conejo, Evaluating alternative offering strategies for wind producers in a pool, Applied Energy 88 (12) (2011) pp. 4918 – 4926.

[34] M. R. Hesamzadeh, M. Yazdani, Transmission capacity expansion in imperfectly competitive power markets, IEEE Trans. Power Syst. 29 (1) (2014) pp. 62–71.

[35] S. J. Kazempour, H. Zareipour, Equilibria in an oligopolistic market with wind power production, IEEE Trans. Power Syst. 29 (2) (2014) pp. 686–697.

[36] M. Zugno, J. M. Morales, P. Pinson, H. Madsen, Pool strategy of a price-maker wind power producer, IEEE Trans. Power Syst. 28 (3) (2013) pp. 3440 – 3450.

[37] L. Baringo, A. J. Conejo, Strategic offering for a wind power producer, IEEE Trans. Power Syst. 28 (4) (2013) pp. 4645 – 4654.

[38] A. A. S. de la Nieta, J. Contreras, J. I. Munoz, M. O'Malley, Modeling the impact of a wind power producer as a price-maker, IEEE Trans. Power Syst. 29 (6) (2014) pp. 2723–2732.

[39] T. Dai, W. Qiao, Optimal bidding strategy of a strategic wind power producer in the short-term market, IEEE Transactions on Sustainable Energy 6 (3) (2015) pp. 707–719.

[40] L. Deng, B. F. Hobbs, P. Renson, What is the cost of negative bidding by wind? A unit commitment analysis of cost and emissions, IEEE Trans. Power Syst. 30 (4) (2015) pp. 1805 – 1814.

[41] F. Foucault, R. Girard, G. Kariniotakis, Wind farm strategic investment considering forecast errors penalties in a nodal prices market, EWEA 2014 (2014) pp. 1–9.

[42] Z. Zhao, L. Wu, Impacts of high penetration wind generation and demand response on LMPs in day-ahead market, IEEE Transactions on Smart Grid 5 (1) (2014) pp. 220–229.

[43] M. Hildmann, A. Ulbig, G. Andersson, Empirical analysis of the merit-order effect and the missing money problem in power markets with high RES shares, IEEE Trans. Power Syst. 30 (3) (2015) pp. 1560–1570.

[44] J. M. Morales, M. Zugno, S. Pineda, P. Pinson, Redefining the merit order of stochastic generation in forward markets, IEEE Trans. Power Syst. 29 (2) (2014) pp. 992–993.

[45] Y. Xiao, X. Wang, X. Wang, C. Dang, M. Lu, Behavior analysis of wind power producer in electricity market, Applied Energy 171 (2016) pp. 325–335.

[46] M. Vilim, A. Botterud, Wind power bidding in electricity markets with high wind penetration, Applied Energy 118 (2014) pp. 141–155.

[47] C. Ruiz, A. J. Conejo, Pool strategy of a producer with endogenous formation of locational marginal prices, IEEE Trans. Power Syst. 24 (4) (2009) pp. 1855–1866.

[48] Reliability Test System Task Force, The IEEE reliability test system-1996, IEEE Trans. Power Syst. 14 (3) (1999) pp. 1010–1020.

[49] L. Baringo, A. J. Conejo, Correlated wind-power production and electric load scenarios for investment decisions, Applied Energy 101 (2013) pp. 475 – 482.

[50] J. M. Morales, R. Minguez, A. J. Conejo, A methodology to generate statistically dependent wind speed scenarios, Applied Energy 87 (3) (2010) pp. 843 – 855.

[51] S. I. Vagropoulos, E. G. Kardakos, C. K. Simoglou, A. G. Bakirtzis, J. P. S. Catalao, ANN-based scenario generation methodology for stochastic variables of electric power systems, Electric Power Systems Research 134 (2016) pp. 9 – 18.

[52] P. Pinson, H. Madsen, H. A. Nielsen, G. Papaefthymiou, B. Klockl, From probabilistic forecasts to statistical scenarios of short-term wind power production, Wind Energy 12 (1) (2009) pp. 51–62.

[53] G. Diaz, J. Gomez-Aleixandre, J. Coto, Wind power scenario generation through state-space specifications for uncertainty analysis of wind power plants, Applied Energy 162 (2016) 21 – 30.

[54] A. Likas, N. Vlassis, J. J. Verbeek, The global K-Means clustering algorithm, Pattern recognition 36 (2) (2003) pp. 451–461.

[55] C. Ruiz, S. J. Kazempour, A. J. Conejo, Equilibria in futures and spot electricity markets, Electric Power Systems Research 84 (1) (2012) pp. 1 – 9.