IMPACT OF FAST WIND FLUCTUATIONS ON THE PROFIT OF A WIND POWER PRODUCER JOINTLY TRADING IN ENERGY AND RESERVE MARKETS

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Abstract

In light of the latest technological achievements in wind farm control, wind power producers (WPPs) are motivated to participate in the joint day-ahead energy and reserve market (JERM) so as to obtain additional revenue by offering ancillary services. However, their expected profit is potentially affected by fast fluctuations of the available wind power in real-time, which may prevent them to deliver the capacity offered at the day-ahead stage. In order to evaluate this impact, a stochastic framework aiming at maximizing the WPP's profit in the day-ahead JERM, based on hourly mean wind power forecasts, is firstly developed. Once the optimal bids are obtained, an empirical ex-post analysis is performed to assess the impact of actual wind speed fluctuations on the WPP's profit. Accordingly, the resulting revenue streams from the different market floors are separately compared to their related expected values, so as to determine the losses regarding the inability of both reserve capacity procurement and activation as well as deviations from the scheduled energy. The outcomes confirm that wind speed fluctuations have a significant impact on the WPP's ability to deliver the scheduled reserve, thus negatively impacting its actual profit.

1 Introduction

The uncertain nature of wind speed accompanied by a high level of wind power integration in electrical grids introduces new challenges for a secure and reliable operation of power systems [1]. New structures and rules are thus continuously emerging to accommodate the uncertain and fluctuating wind generation in the liberalized competitive framework. In this direction, various market floors such as day-ahead energy and reserve markets, which are complemented with a real-time balancing stage, are designed. In that context, similar to the other market participants, wind power producers (WPPs) are looking toward maximization of their profit through optimal bidding strategies in the different market floors [2].

In [3], by using a bivariate distribution of real-time market price and a wind power forecast error, an optimal offer-curve for a WPP taking part in the day-ahead energy market is drawn so as to maximize its profit. The optimal bidding strategy of WPPs using a bi-level stochastic model is investigated in [4], in which the authors also considered the operation of other energy sources in the real-time market. In [5], a bidding strategy is introduced so as to minimize the imbalance costs of WPPs in the real-time market, while wind power forecast error is presented as a stochastic parameter. In [6], in order to maximize the WPPs' profit, a stochastic model is introduced to reduce deviations from the scheduled power. The authors reflected the uncertainties associated with wind power production and market fees in their model.

It should be noted that the aforementioned papers merely considered the participation of WPPs in the day-ahead energy market while minimizing the imbalance costs. However, thanks to new technological achievements in wind farm control and recent evolutions in the reserve markets, WPPs are potentially able to provide ancillary services such as frequency containment reserve (FCR) [7-9]. However, since wind power generation has nearly zero marginal cost, offering downward reserve regulation is not profitable for WPPs, in contrast to conventional power plants that leverages important fuel savings. Therefore, market policies should either allow provision of asymmetric services or involvement with an aggregator to promote WPPs to take part in the reserve market.

Several studies are conducted to consider the potential partaking of WPPs in the reserve market as well as the energy market [1,7-8]. For instance, a joint day-ahead energy and reserve market (JERM) model aiming to increase the WPPs' revenue is proposed in [1]. In this model, penalties regarding the under procurement of the reserve capacity are designed to be sufficiently low so as to avoid the risk of losing revenue in the reserve market. A stochastic model for profit maximization of a WPP playing in the JERM is presented in [7]. In [8], an analytical approach for the participation of WPP in JERM is presented, so as to optimize its expected profit. It is shown that the WPP participation in JERM follows a binary behaviour where it bids either in the reserve or energy market, depending on the market prices and penalty rates.

It should be pointed out that the actual wind capacity available in real-time, accounting for inherent fast wind speed fluctuations, is not considered in these studies. Such models thereby fail to capture penalties arising from the WPP inability to deliver the capacity offered at the day-ahead stage, which may potentially lead to ex-post disappointment regarding the actual profit.

In this paper, we aim at properly evaluating this impact. To that end, we firstly formulate the day-ahead problem of a WPP targeting to maximize its profit in the JERM. Without loss of generality, in the same fashion as [3,6-8], the WPP is considered to be a price-taker in the electricity markets. It signifies that the power generated by the WPP has no effect on market prices, which is a reasonable assumption since the generation of a single WPP is dramatically smaller than the total generation at the system level. Thereafter, in order to investigate the impact of actual intra-period wind speed fluctuations on the obtained results, two different cases are considered. In the first one, we consider a single scenario that represents the actual perfect information of the mean wind power (over each time step of the daily optimization horizon). This case shows that, even if a WPP relies on perfect information on the averaged future wind conditions, the intra-period wind fluctuations, which is considered to be 10 sec in this study, can negatively affect its revenues. The second case is modelled as a more realistic two-stage stochastic model, where wind speed uncertainties are represented through a set of scenarios. In the presented formulation, the WPP is not allowed to deviate from the contracted reserve capacity, thus leading to conservative strategies in the reserve market.

After obtaining the optimal bids in both aforementioned cases, an ex-post analysis is performed. The proposed ex-post analysis employs a set of 15-min synthetic wind speed signals with a 10-sec resolution as well as a set of real-world system frequency data (to represent the real-time activation of balancing reserves). The numerical analysis illustrates the consequences of intra-period wind speed fluctuations in providing the balancing reserve, as well as the resulting effects in the WPP's expected inflows and losses. The revenue streams in the different market floors are individually compared to their associated expected terms.

The remaining part of the paper is outlined as follows. In section 2, the proposed stochastic model for the participation of WPP in JERM is presented. Section 3 explains the proposed empirical ex-post analysis and assessment approach. In section 4 the numerical results are detailed. Finally, the last section, concludes the paper with some guidelines for the participation of WPPs in the JERM.

2 Model Description

2.1 Electricity market structure

Within the current electricity market structure, WPPs are able to participate as a balance responsible party (BRP) in the day-ahead energy market and submit their bids. However, any imbalance (on a specific period) from the nominated bids is penalized by the transmission system operator (TSO). The imbalance settlement price mechanism varies in different market structures [10, 11]. In this paper, a two-price settlement scheme is considered, where positive and negative imbalances are penalized at different prices, with the goal of incentivizing agents to keep a perfect balance within their portfolio. In case of residual imbalance at the system level, the TSO activates the balancing offers purchased in the day-ahead reserve market.

The reserve market contains different services, which are classified in regards to their response speed. In this paper, we focus on the provision of frequency containment reserve (FCR), which is automatically activated in a decentralized way for quickly alleviating momentary frequency deviations. Depending on market policies, FCR can be remunerated in form of both power and energy [12]. In other words, these services are paid for the allocated capacity, while their actual activation is paid as an energy service. It should be noted that some markets only pay the FCR service for the availability of the power capacity. However, in order to promote renewable generation to take an active role in the reserve market, new policies may adapt to pay for the activated energy as well.

2.2 Stochastic model formulation

In this section, a stochastic framework is presented to assist WPPs to find the optimal trade-off between energy and reserve in JERM. The mathematical formulation of this problem is expressed as follows:

$$\text{Max:}\Pi = \lambda^{CE}P^{CE}\Delta t + \lambda^{CR}R^{CR} + \sum_{\omega\in\Omega}\xi_\omega\{\lambda^{\uparrow}\Delta P_\omega^{\uparrow} - \lambda^{\downarrow}\Delta P_\omega^{\downarrow} + \lambda^{R+}\theta_\omega\tilde{R}_\omega\}\Delta t \quad (1)$$

Ψ

$$P^{CE} + R^{CR} \leq P_{max} \quad (2)$$

$$P^{CE} + R^{CR} \geq P_{min} \quad (3)$$

$$\tilde{P}_\omega + \tilde{R}_\omega = \tilde{\Gamma}_\omega \qquad \forall\omega\in\Omega \quad (4)$$

$$\widetilde{\Delta P}_\omega = P^{CE} - \tilde{P}_\omega \qquad \forall\omega\in\Omega \quad (5)$$

$$\widetilde{\Delta P}_\omega = \Delta P_\omega^{\downarrow} - \Delta P_\omega^{\uparrow} \qquad \forall\omega\in\Omega \quad (6)$$

$$R^{CR} - \tilde{R}_\omega \leq 0 \qquad \forall\omega\in\Omega \quad (7)$$

$$P^{CE}, R^{CR}, \tilde{P}_\omega, \tilde{R}_\omega, \Delta P_\omega^{\uparrow}, \Delta P_\omega^{\downarrow} \geq 0 \qquad \forall\omega\in\Omega \quad (8)$$

where the objective function Π, presented in (1), consists of 2 contributions for the first (day-ahead) stage and 3 terms for the second (real-time) stage. The first term represents the income of the WPP in the day-ahead energy market. In that regard, $\lambda^{CE}, P^{CE}, \Delta t$ denote the day-ahead energy price, the contracted power and the imbalance period (in hour unit), respectively. The second term represents the income for procurement of the reserve capacity, which depends on the reserve capacity procurement price λ^{CR}, and the contracted reserve capacity R^{CR}. The real-time contributions are weighted by scenario $\omega \in \Omega$, where ξ_ω is the probability of each scenario. The third and fourth terms indicate the imbalance settlement, where $\lambda^{\uparrow}$ and $\lambda^{\downarrow}$ denote the imbalance price associated with a power surplus $\Delta P_\omega^{\uparrow}$ and power deficit $\Delta P_\omega^{\downarrow}$ with respect to the day-ahead contract, respectively. The last term in (1) determines the payment of reserve power activation, where λ^{R+} and θ_ω represent the reserve activation price and the percentage of real-time reserve deployment $\tilde{R}_\omega$, respectively (see section 3.2).

Constraints (2) and (3) guarantee that the total contracted bid in the energy and reserve markets is bounded by the physical generation limits of the wind farm. Constraint (4) entails the allocated power in the energy market $\tilde{P}_\omega$ and the reserve market $\tilde{R}_\omega$ to match the total available power $\tilde{\Gamma}_\omega$ in each scenario. Constraint (5) determines the total power deviation in each scenario $\widetilde{\Delta P}_{\omega}$. Constraint (6) allows $\Delta P_{\omega}^{\downarrow}$ to be the deficit of power in case of real-time generation shortage and $\Delta P_{\omega}^{\uparrow}$ to be to the surplus of generation in case of over generation. Constraint (7) ensures that violation of the scheduled reserve (and its demanded activation) does not occur. Constraint (8) guarantees that the employed optimization variables, i.e. $\Psi = \{P^{CE}, R^{CR}, \tilde{P}_{\omega}, \tilde{R}_{\omega}, \Delta P_{\omega}^{\uparrow}, \Delta P_{\omega}^{\downarrow}\}$, are non-negative. The subscript ω in Ψ denotes the second stage decision variables. Additionally, the random variables θ_{ω} and $\tilde{\Gamma}_{\omega}$ introduce the uncertainties in the model.

It is worth noting that the expected values of market prices are substituted by their random distribution in this model. Due to certainty equivalent theory, this assumption is valid as these prices enter linearly in the objective function and are not influenced by the WPP generation [8]. Moreover, the presented model (1)-(8) considers one imbalance settlement period for sake of simplicity and reducing the computational burden. Nonetheless, the information regarding market prices and scenarios could be dynamically updated so as to obtain the optimal bids of the succeeding time units.

3 Empirical ex-post analysis

In this section, the proposed ex-post analysis approach is described to assess the impact of the fast wind speed fluctuations on the actual WPP profit.

3.1 Energy market and imbalance settlement

The TSO imposes an imbalance fee on BRPs violating their scheduled power bids on the energy market. In this paper, the imbalance settlement of energy takes place at the end of each quarter-of-an-hour, i.e. Δt = 1/4 h. Thus, for each of the 96 daily periods, depending on the system requirements for upward or downward regulation, an imbalance price is determined, which reflects the real-time value of energy. In order to assess the actual revenue of the WPP, the obtained results of the stochastic model and engaged imbalance prices (defined in section 2), along with real-time available power are employed.

At each settlement period, when the mean observed power P^{obs} is higher than the scheduled power in the energy market P^{CE}, the WPP gets paid for its positive deviation as follows:

$$\Pi^{+} = \Delta t(P^{obs} - P^{CE})\lambda^{\uparrow} \tag{9}$$

Consequently, the actual WPP's revenue for participating in the energy market is determined as follows:

$$\Pi^{DAB} = \lambda^{CE}\Delta t P^{CE} + \Pi^{+} \tag{10}$$

Accordingly, the loss of profit when trading the surplus of power by the imbalance settlement price rather than the day-ahead market price, so-called opportunity cost, is yielded as follows:

$$\Pi^{op} = \Delta t(P^{obs} - P^{CE})(\lambda^{CE} - \lambda^{\uparrow}) \tag{11}$$

On the contrary, when the mean available power is lower than the scheduled energy in the energy market, the WPP is responsible for its deficit of generation. The payment for compensating the negative deviation is expressed as follows:

$$\Pi^{-} = \Delta t(P^{obs} - P^{CE})\lambda^{\downarrow} \tag{12}$$

Consequently, the income and opportunity cost of the WPP for participating in the energy market is determined by (13) and (14) respectively, as follows:

$$\Pi^{DAB} = \lambda^{CE}\Delta t P^{CE} + \Pi^{-} \tag{13}$$

$$\Pi^{op} = \Delta t(P^{obs} - P^{CE})(\lambda^{CE} - \lambda^{\downarrow}) \tag{14}$$

3.2 Reserve and balancing markets

The settlement period for procurement and activation of the reserve is equal to 10 seconds (which is shorter than the 15 minutes of the imbalance energy settlement). The percentage of FCR to be automatically activated by the TSO is a function of the system frequency deviation, Δf, as shown in Fig 1 It can be seen that when $-0.01 \leq \Delta f \leq 0$ FCR is not activated, while all contracted FCR capacity is activated for $\Delta f < -0.2$. In the range $-0.2 \leq \Delta f \leq -0.01$, the percentage of the activated FCR θ is linearly proportional to Δf. The same scheme, though with a negative sign, is applied for downward FCR activation.

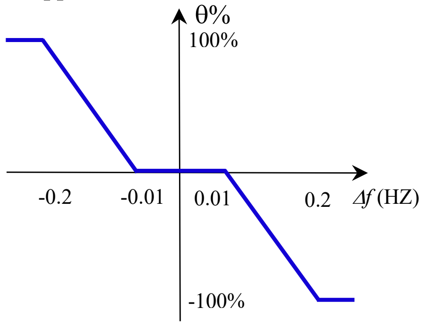

Fig 1. Percentage of FCR activation with respect to Δf

The WPP's net revenue for procuring reserve capacity Π^{cap} is computed over each 10-second interval δt as follows:

$$\Pi^{Cap} = R^{CR}\lambda^{CR} - \frac{\delta t}{\Delta \acute{t}}\sum_{i=1}^{\Delta \acute{t}/\delta t} R^{CR}\lambda^{CR}\mathbb{I}(P_i^{obs} < R^{CR}) \tag{15}$$

In (15) Π^{cap} consists of two terms including the expected revenue of the WPP for reserve capacity procurement (first term) and the penalty for not being able to meet the contracted reserve capacity in real-time (second term). In this regard, the binary variable $\mathbb{I}$ is equal to 1 when the stated condition in the bracket is satisfied, i.e. observed power being less than the contracted FCR. The constants $\Delta t'$ and δt represent the energy and reserve imbalance settlement periods in seconds, respectively.

Additionally, the balancing revenues Π^{act} for FCR activation is expressed as follows:

$$\Pi^{act} = \Delta t\frac{\delta t}{\Delta \acute{t}}\sum_{i=1}^{\Delta \acute{t}/\delta t} R^{CR}\theta_i\lambda^{R+}\mathbb{I}(P_i^{obs} \geq R^{CR}) \tag{16}$$

where λ^{R+} is the price of reserve activation.

Additionally, the WPP is penalized when failing to meet the contracted or demanded reserve as follows:

$$\Pi^{R-} = -\Delta t\frac{\delta t}{\Delta \acute{t}}\sum_{i=1}^{\Delta \acute{t}/\delta t} R^{CR}\theta_i\lambda^{R-}\mathbb{I}(P_i^{obs} < R^{CR}) \tag{17}$$

where λ^{R-} is the penalty price used in reserve imbalance settlement. It should be noted that, in this mechanism, the WPP should at least provide the contracted reserve capacity in order to get paid for its activation. In other words, the penalty term (17) is applied when the WPP is unable to provide (in real-time) the reserve capacity scheduled in day-ahead.

4 Numerical Results

The proposed stochastic model and ex-post analysis are implemented in Julia/JuMP [13] and Python. In this study, a 5 MW wind turbine model is used for simulations. Table 1 summarizes the market prices and penalty rates used to evaluate the WPP profit. Additionally, two cases are established to investigate the impact of intra-period wind speed fluctuations on WPP's profit. The first case assumes that the perfect information of mean wind power for each quarter-hour is available through an ideal forecaster. On the other hand, the second case considers a set of scenarios to represent the mean wind speed uncertainty. Particularly, the stochastic process of wind speed is simulated through an ARMA scenario generation method. The detail of the applied method is explained in [10]. Once the associated parameters of the ARMA model are obtained, a set of 1000 scenarios, covering the interval between the day-ahead market closure gate and the first quarter-hour of the next day, is generated. Afterwards, the scenario set related to the last quarter-hour is reduced by a scenario reduction technique based on the Kantorovich distance [10]. The reduced set of mean wind speed scenarios is converted to wind power by using the corresponding power curve of the wind turbine.

For both cases, an additional set of scenarios, characterizing the system frequency is produced by sampling over the historical data of the last 30 days. These scenarios are reduced with the same scenario reduction method. The selected scenarios are used to calculate the percentage of the actual balancing energy activated in real-time, as described in section 4.2 and depicted in Fig 1. In the following, the results are firstly discussed through an illustrative example that enables to qualitatively focus on the effects of fast wind fluctuations on a single ex-post scenario. Secondly, an extensive out-of-sample analysis is carried out to properly quantify the financial effects in a multi-scenario probabilistic environment.

Table 1 Prices and penalty rates of the market

λ^{CE}	λ^{CR}	$\lambda^{\uparrow}$
30-50	28	30
$\lambda^{\downarrow}$	λ^{R+}	λ^{R-}
50	50	150

4.1 Illustrative example

4.1.1 First case: In this case, a single scenario representing the perfect information on the mean wind power along with a set of scenarios representing the percentage of the activated reserve is fed to the stochastic model. Since there is no uncertainty related to the real-time wind availability, the WPP allocates all the forecasted power in the reserve market, i.e. R^{CR}= 0.8028 MW, since prices are more beneficial than in the energy market. Therefore, the WPP receives a constant income, i.e. Π = 23.26 EUR, for playing in the reserve market.

For the sake of illustration, one synthetic wind speed signal, with the same mean as the actual speed (i.e., 5.7 m/s), is generated. The synthetic wind speed signal is then converted to wind power using the power curve of the wind turbine as shown in Fig 2 (plain line). In parallel, the real-time amount of activated FCR is simulated by using the system frequency data for the period of interest, as shown in Fig 3 Interestingly, we observe that, due to fast (10-sec) wind speed fluctuations and the required level of reserve activation, the WPP is not able to provide the contracted reserve capacity for several intervals δt, thereby losing 55.56% of its expected profit. In Fig 4, the instantaneous net revenue of the WPP for reserve activation is normalized by the value determined by the day-ahead optimization (plain line).

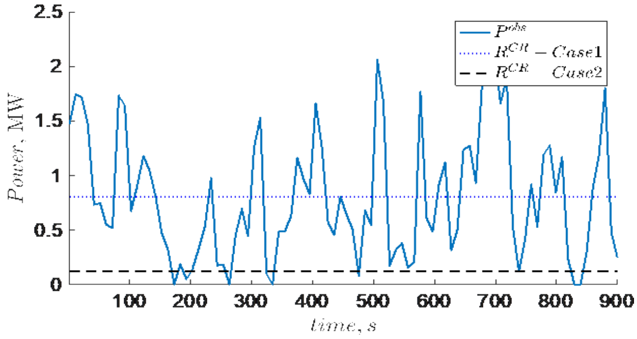

Fig 2. Observed power (plain line), contracted FCR for case 1(dotted line), contracted FCR for case 2 (dashed line)

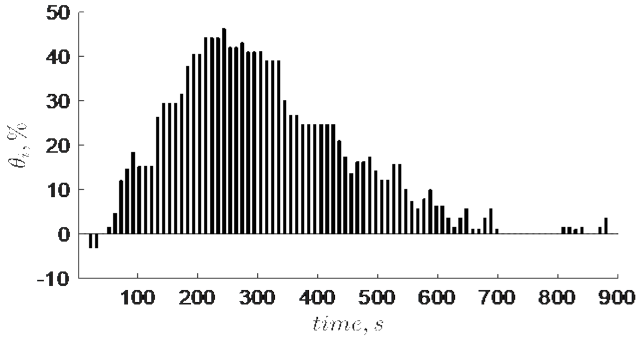

Fig 3. Required level of FCR activation

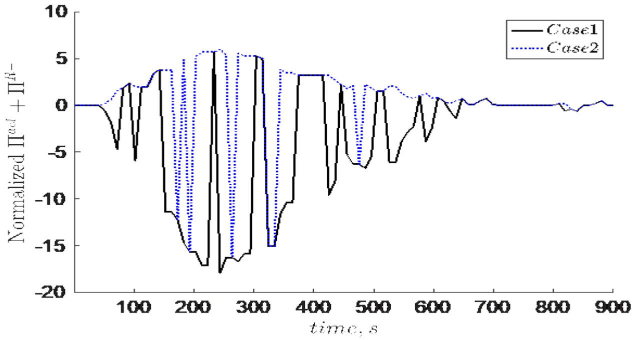

Fig 4. Normalized net reserve activation revenue

4.1.2 *Second case:* A set of scenarios regarding the mean wind speed and percentage of the activated reserve is fed to the stochastic model (1)-(8). The obtained expected revenue and optimal bids of the WPP for a range of spot market prices are shown in Fig 5. It is seen that the WPP allocates a constant feasible power in the reserve market, and devotes the rest in the energy market. In this way, the WPP avoids the risk of deviation from the contracted reserve capacity. The same simulated wind speed signal and system frequency data are used for ex-post analysis. It is seen that the available mean power may differ from the power bids of the energy market. As a consequence, imbalance penalties (opportunity costs), as defined in Section 3.1, are occurring. The actual revenue of the WPP in the energy markets (Π^{DAB}) along with the opportunity

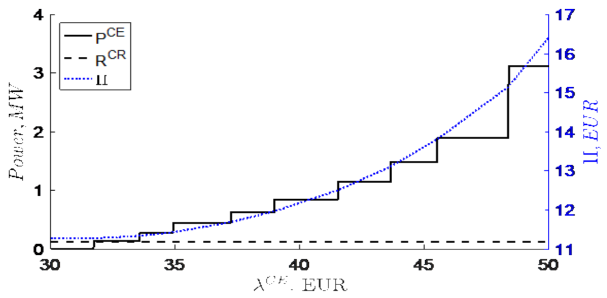

Fig 5. (left axis) optimal bids, (right axis) expected revenue

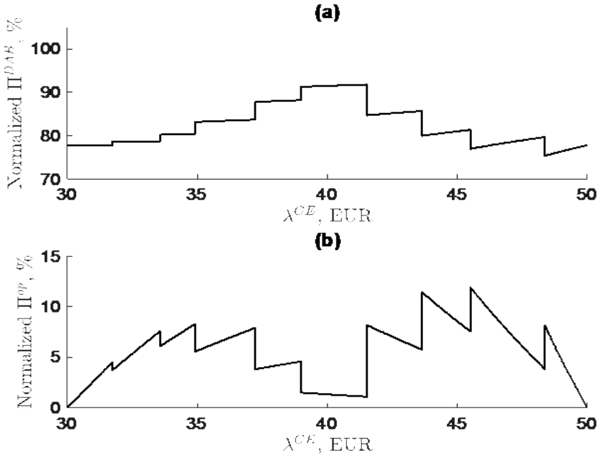

Fig 6(a)-(b). (a) Normalized Π^{DAB}, (b) Normalized Π^{op}

cost (Π^{op}) are normalized by their related expected term, and shown in Fig 6(a)-(b), respectively. One can see that the actual revenue of the WPP in the energy market may deviate more than 20% from the expected value (obtained at the end of the day-ahead optimization). Moreover, the WPP may face an opportunity cost of more than 10% with respect to its related expected income.

Furthermore, for some 10-sec intervals, the wind speed drops sufficiently low so that the WPP fails to deliver the FCR capacity offered in day-ahead. Therefore, the revenues from the reserve market also deviate from the expected ones. In this regard, the actual revenue of the WPP for reserve capacity procurement is 10% lower than the related income of the day-ahead stage. Moreover, the normalized actual net revenue from the reserve deployment is shown in dotted line in Fig 4.

4.2 Out of sample analysis

The obtained results in Section 4.1 merely describe the impact of wind speed fluctuations on the WPP's profit based on one realization of wind speed and system frequency data for a quarter-hour. Hence, to correctly assess the impact of wind speed fluctuations on the obtained results of the stochastic model, a broader representation of possible realizations of wind speed and system frequency should be employed for the ex-post analysis. In this regard, 100 wind speed signals and system frequency data are exploited to generate 10,000 different samples.

4.2.1 First Case: The same expected profit and bids regarding the perfect information of the available mean power as section 4.1.1 are considered. The normalized mean value of the instantaneous net reserve activation revenue with respect to the produced samples is shown in Fig 7 (plain line). Additionally, the standard deviation for each instance is shown by blue bars in Fig 7. It is seen that on average, the WPP is not able to meet the required reserve activation since the plain curve is below zero. In Table 2, the first row summarises the average of the normalized revenue elements of the WPP for taking part in the reserve market. As shown in this Table, regarding the real-time reserve activation, the WPP receives a negative revenue (i.e., payment to the TSO) equal to -33.77% of its associated expected term. Additionally, on average the actual revenue for reserve capacity procurement is only 42.14% of its expected one (i.e. 57.86% lower). The overall revenue of the WPP regarding activation and procurement of reserve is 39.60% of its expected value (i.e. 60.40% lower).

4.2.2 Second case: In this case, the obtained results of the stochastic model regarding scenarios of mean power, i.e. as detailed in 4.1.2, are employed. Referring to the energy market, due to the fluctuations of wind speed, the WPP losses parts of its revenue with respect to its expected value. The normalized actual revenue of the WPP resulting from the energy market and imbalance settlement (Π^{DAB}) is shown in Fig 8(a). The plain line is the mean value of Π^{DAB} over the samples and the blue bars show the standard deviations. As seen in Fig 8(a), referring to the Π^{DAB}, on average WPP losses between 2.27% to 19.09% of its expected revenue. Similarly, Fig 8(b) shows the mean and standard deviation of normalized cost of opportunity over the samples. It is seen that the cost of opportunity is between 1.01% to 11.03% of the expected revenue for participation in the energy market and imbalance settlement.

Additionally, the WPP faces many periods during which it is unable to procure or activate the required FCR. Thus, the actual revenue elements of reserve markets deviate from the expected ones. In Fig 9, the mean and standard deviation of the normalized net reserve activation revenue are plotted by a plain line and blue bars, respectively. The second row in Table 2 expresses the average of the normalized revenue streams of the WPP for taking part in the reserve market. As shown in this Table, due to the wind speed fluctuations, regarding the

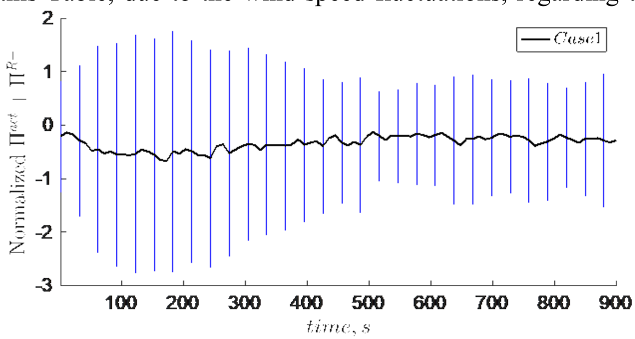

Fig 7. Normalized net reserve activation revenue and its standard deviation concerning out-of-sample analysis

Table 2. Normalized revenue elements of the reserve market

	$\overline{\Pi^{act}+\Pi^{R-}}$	$\overline{\Pi^{cap}}$	$\overline{\Pi^{act}+\Pi^{R-}+\Pi^{cap}}$
Case 1	-33.77%	42.14 %	39.60 %
Case 2	13.79 %	88.26 %	85.77%

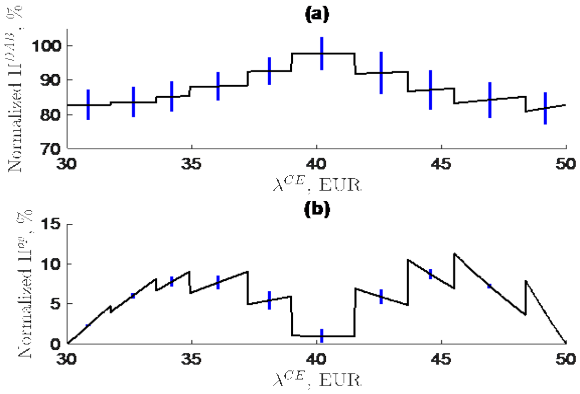

Fig 8(a)-(b). (a) Normalized Π^{DAB}, (b) Normalized Π^{op}

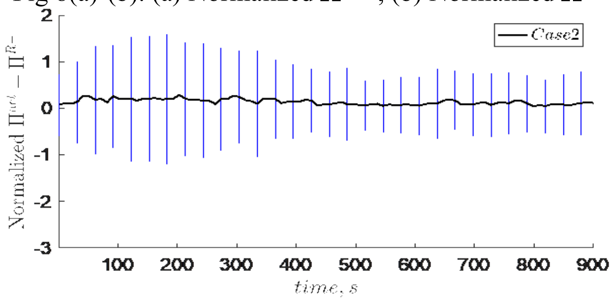

Fig 9. Normalized net reserve activation revenue and its standard deviation concerning out-of-sample analysis

real-time reserve activation, the WPP only receives 13.79% of the associated expected term. Additionally, on average the actual revenue for reserve capacity procurement is 88.26% of its expected one (i.e. 11.74% lower). The overall revenue of WPP regarding activation and procurement of reserve is 85.77% of its expected value (i.e. 14. 23% lower).

5 Conclusion

In this paper, the impact of intra-period wind speed fluctuations on the profit of a WPP participating in JERM is assessed. Practically, a stochastic model for the WPP participation in JERM is primarily developed. Afterward, an ex-post analysis considering two cases including perfect wind power information and wind speed forecast scenarios is performed. Despite using a risk-averse model in dealing with the reserve power violation, the numerical outcomes for both cases confirm that the revenue considerably deviates from its expected value. Additionally, it can be seen that the day-ahead uncertainty of the expected (mean) wind realization (case 2) inadvertently helps the WPP to hedge against intra-hour wind speed fluctuations (compared to case 1). However, decision-makers should not be misled to use a forecaster with a wide range of uncertainty to handle the uncertainty of wind speed fluctuations. On the other hand, they should be cautioned that even exploiting a perfect mean wind power forecaster does not essentially help them to play optimally in JERM. Therefore, as planned in our future research works, decision-makers should devise new models to better reflect the intra-period wind speed fluctuations in their stochastic optimization framework. Moreover, developing short term probabilistic forecast tools to capture wind speed variability is another avenue for future research works [14].

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