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Optimal Energy Bidding for Renewable Plants: A Practical Application to an Actual Wind Farm in Spain

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Abstract

Finding an optimal bidding strategy for a wind farm in the electricity market is not straightforward due to the wind variability. This issue is becoming more relevant as renewable plants are more exposed to market signals. Considering the characteristics of the European markets, operators must submit the energy bidding between 12-36 hours ahead the actual delivery time. This bidding can be adjusted later in any session of the intraday markets, but sometimes this is not enough to reduce significantly the deviation risk. This paper presents a practical application of a method to analytically calculate the optimal bidding of a wind power plant, based on the maximisation of the income function. The results show that, given the characteristics of the deviation markets in Spain, the optimal bidding strategy depends essentially on the deviation of the system. The proposed technique has been tested and validated in a real application by considering actual data for energy production and forecasts for an operating wind farm in Spain, as well as real market deviations and prices provided by the Spanish system and market operators; analysing the advantages of the proposed optimal bidding strategy over the most plausible option, based on bidding the forecasted energy.

Keywords: electricity balancing markets, electricity day-ahead market, wind power bidding, wind energy

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Nomenclature

WFO:	Wind Farm Operator
WF:	Wind Farm
VPP:	Virtual Power Plant
PPA:	Power Purchase Agreement
PDF:	Probability Density Function
SCADA:	Supervisory Control and Data Acquisition
MEC:	Ministry of Economy and Competitiveness
DK:	Denmark
UK:	The United Kingdom
US	The United States
DAM:	Day Ahead Market
IM:	Intraday Market
RTM	Real Time Market
BM:	Balancing Market
BS:	Balancing Services
t:	Dispatching Time
k:	Lead Time
$E_f(t)$:	Production forecast for hour (t)
$E_p(t)$:	Energy output for hour (t)
$E_b(t)$:	Energy bid for hour (t)
$F(E_b)$:	Probability of producing an energy output less or equal to E_b
B:	Expected income
λ:	Day-ahead market price
β:	Probability of a positive system´s deviation
$\boldsymbol{C_p^+}$:	Cost of a positive deviation being positive the deviation of the system
$\boldsymbol{C_p^-}$:	Cost of a negative deviation being positive the deviation of the system
$\boldsymbol{C_n^+}$:	Cost of a positive deviation being negative the deviation of the system
$\boldsymbol{C_n^-}$:	Cost of a negative deviation being negative the deviation of the system
u:	Generation Unit
s:	Market Session
z:	Regulation Zone
b:	Bid Block
i:	International Interconnection
$NBEUD$:	Net balance of assigned energy upward and downward of the balancing services
$AEIMU_{u,s}$:	Assigned energy upward by the imbalance management procedure
$AEIMD_{u,s}$:	Assigned energy downward by the imbalance management procedure
$AETERU_u$:	Assigned energy by tertiary reserve upward
$AETERD_u$:	Assigned energy by tertiary reserve downward
$AESECU_z$:	Assigned energy by secondary reserve upward
$AESECD_z$:	Assigned energy by secondary reserve downward
$EIIB_{i,b}$:	Energy imported
$EEIB_{i,b}$:	Energy exported
$MPDAM$:	Marginal price of the day-ahead market
$WAPU$:	Weighted average price of the energies upward on the imbalance management, secondary and tertiary reserve.
$WAPD$:	Weighted average price of the energies downward on the imbalance management, secondary and tertiary reserve.

1. Introduction

The main challenge for the participation of wind energy plants in a liberalized market is the variable behaviour of wind speed. In Europe, the European Commission's new legislative package on the rules for the functioning of the internal electricity market aims at moving towards a market design that facilitates the integration of renewables into an electricity system with an increasing presence of variable generation sources. However, the current design of most European markets requires generators to submit their bids on the day-ahead market (DAM) around 24 hours in advance, a lead time in which forecast uncertainty about actual production by wind generators is still high. For example, to participate in the Iberian DAM (the Spanish and Portuguese electricity markets are integrated into a single Iberian market, which is also part of the Internal European electricity market), it is necessary to submit a bid 12-36 hours prior to the actual dispatching time [1]. This bidding could be adjusted later in the intraday market (IM), but even in this market the wind farm operators (WFO) must send their bids 3-14 hours before. These are lead times in which wind forecasts still have a relatively high degree of uncertainty, which implies a certain level of risk associated with the participation of wind plants in electricity markets, as deviations from the bid are penalized. This represents a difficult situation for wind farms to participate in liberalized electricity markets under the same conditions as conventional generators.

The existing literature on the impact of weather forecast of renewable plants on DAMs participation is extensive. The authors would like to refer to [2–4] for a thorough review on this subject. Ahmed et al. presented in [2] a very deep analysis of forecasting of different aspects of power systems such as forecasting in renewable power dispatch, forecasting for energy storage systems, impact of forecasting uncertainties in energy markets, forecasting in reserve size estimation, etc. Jónsson et al. [3] describe the impact of wind power forecasts on the electricity markets. WFs are considered as price maker in that work, considering its potential effects on prices in areas where wind power has a high penetration and share a considerable amount in the generation mix. The influence of wind power forecast in prices is analysed in the Western Danish price area (DK-1) of Nord Pool´s Elspot market. The authors demonstrated that the ratio between the forecasted wind power generation and the forecasted load has a strong association with the spot prices. Zhang et al. [4] surveyed the state-of-art methods and new developments in wind power probabilistic forecasting. In that work, the forecasting methods are classified into three categories in terms of uncertainty representation: probabilistic forecast, risk index forecast, and space time scenario forecast. The authors stated that the two main sources of uncertainty in wind power forecast are the variability in wind speed and wind-to-power curves. The three aforementioned papers conclude that the uncertainty on the forecast of wind power production increasingly affect not only the market prices. Facing the difficulty of reducing this uncertainty in its own way, one solution would be the hybridization. Some authors have investigated on the potential of hybridizing wind farms with other type of technologies in order to increase the participation of wind farms in deregulated electricity markets. Mengxuan Lv. et al. [5] presented a review on optimal dispatch of VPP and the optimal bidding of this kind of plants has been explored. Dhillon et al. analysed in [6] the operation in deregulated markets and balancing services of a hybrid wind-pumped storage plant. This type of plant could help to increase the wind power penetration in the electric power systems due to its maturity and large storage capacity. In this same line of research Moghaddam et al. [7] presented a two-stage stochastic programming model based on profit maximisation for the participation in the day-ahead for a combined wind-hydro system. The results obtained by the authors highlight the importance of the chosen penalty market mechanism in the optimal supply strategy by renewable generators. Laia et al. [8] presented also a combined bidding strategy for WFs and thermal units by means a stochastic mixed-integer linear programming approach, showing the potential of the proposed method to maximize the income obtained through the joint participation of both technologies in the market.

WF aggregation would be another feasible solution to increase its benefits by mitigating forecasts uncertainty. Authors in [9,10] have explored this possibility. Baeyens et al. analysed in [9] the benefits of a coalitional bidding of a group of WF in a two-settlement market. The option of bidding in DAM and real time markets (RTM) is considered as well. The imbalance prices are modelled as random non-negative variables. Three different strategies are proposed by Guerrero-Mestre [10] in order to calculate the optimal bidding of a group of WF: (i) each WF offer their energy separately, (ii) each WF offer their energy separately but imbalances are compensating among the WF, and (iii) all WF makes a joint offer to the DAM market. The problem is modelled as a stochastic mixed integer linear programming. Conditional value at risk is included in the objective function as well as the sum of the expected profit.

Other solution to increase the incomes of a wind farm in liberalized markets is adjusting the bids as close as the time to produce the energy. Of course, not all markets have the same characteristics. This bidding strategy has been analysed in [11–13]. In [11] Usaola and Moreno consider the bids made in the day ahead market, and the uncertainty in the power production to adjust the bid in the IM market. In this way, improving the active power forecast could reduce the penalties incurred in. The authors also explored the uncertainty in prices, considering two types of probability density functions (Normal, and Gamma). Three different approaches were considered to calculate the IM offer: (i) participation in the IM is not allowed (worst scenario, whose results are taken as a reference for comparison with the remaining scenarios), (ii) participation in the IM is allowed and the best forecast available is bid in the IM, in this case the revenues are 0.8% higher than the worst scenario and (iii) participation in the IM is allowed and the bid in the IM is based on the proposed approach by authors considering the uncertainties of the wind power forecast, in this case the obtained revenues were 8.5% higher than the worst case. Additionally, authors also analysed the behaviour of the proposed approach by using also a forecasting tool for the IM prices, the revenues obtained in this case were 0.3% higher than the worst scenario. The authors stated that have faced high difficulties to predict the imbalance prices. Therefore, they have multiply by a fix factor the monthly average of the DAM in order to calculate the imbalance prices. In [12] Usaola and Angarita also considered the imbalance costs, by following a similar approach as in [11], but analysing different theoretical prices for buying and selling energy in the balancing market (BM). These prices were calculated by multiplying the DAM prices by a factor and considering the influence on the revenues when varying this factor. The results obtained ranged between 4.26% and 7.83% of improvement when buying price were higher than the selling price. When buying price were lower than selling price, the revenues obtained were between -3.93% and 30.85% higher than the reference scenario. In [13] Bueno et al. focused on the calculation of the IM bid analysing in detail the IM prices. The formulation of this paper is based on the formulation in [11]. The authors have concluded that the uncertainties in the IM prices makes not possible to use forecasted values of this variable to improve de revenues due to the high volatility of this variable, then they have considered perfect information. Imbalance prices have been calculated by multiplying the DAM price by a fixed factor.

A different approach was presented by Holttinen in [14] by analysing the influence of the wind power generation forecast and the lead time to submit the bid. On one side, different time horizons to make the bid were analysed. On the other hand, two scenarios are studied: (i) individual WF bidding or (ii) aggregated bidding in case of being more than one WF. The method was applied in the Nordpool electricity market in the Nordic Countries.

The short-term energy markets participation is analysed in [15–18]. In [15] Pinson et al. presented a methodology to determine the optimal strategy based on modelling the bidding sensitivity against balancing costs generation forecasts. The authors calculated and compared the market value using different forecast methods and the associated bids using different optimization algorithms. Four methods for predicting the imbalance costs were analysed and compared with perfect forecasts in the Dutch electricity pool. They have obtained an 16.41% of improvement with respect to the Persistent method in the best of the cases. Bathurst et al. [16] applied Markov Probabilities to determine the best bidding strategy for a WF in the UK. They showed the effect of market closure delay and forecast window length on imbalance costs of the WF. A method to minimize the imbalance costs was presented by Matevosyan and Söder in [17]. Stochastic programming (a mixed integer algorithm) is used to generate optimal bids of wind energy generation for short-term markets. Forecasting errors of WF output energy are considered as stochastic parameters. The author Afshar et al [18] developed an optimal bidding strategy based on a bi-level approach optimised by a Particle Swarm Optimisation algorithm, the authors modelled the punitive effect of trading in balancing market by considering the prices of this market as a factor of the day-ahead market prices. Then the optimal offer for the balancing market is calculated. The results were tested in the three-bus test system and the IEEE 24-bus test system.

Finally, with regard to analytical approaches based on the probability density function (PDF) of energy forecasts to optimise the bidding strategy, Morales et al. presented in [19] a method to determine the optimal trading strategies for renewable energy plants in electricity markets. That work presented optimal strategies to participate in the DAM and BMs considering both deterministic and stochastic prices. The relation between these both markets is analysed in order to make arbitrage between them, that is that the optimal bid in the (BMs) is normally influenced by the bid made in the DAM. However, it should be mentioned that the results presented are based on a conceptual approach and not on a numerical one. Authors in [20,21] have gone a step further making a detailed analysis for different scenarios on the optimal bidding subject. Analytical results using Great Britain market data has been presented by Dent et al. in [20]. The authors considered different scenarios to calculate the optimal bidding. They have only taken into account the WF production and the real-time prices which are in fact related to DAM prices. Markets with a single and double imbalance prices are analysed. The influence of the conventional generation in the bid is analysed when the wind farm production and the real time prices are correlated. In [21], Bitar et al. has presented an analysis of different problems regarding the optimal bidding and the influence of forecasting uncertainties with the market prices. In the paper the possibility of adjusting the bidding in the IM is considered. Additionally, the authors proposed of installing a small thermal plant along with the WF to cope with its negative imbalance. In this way they have analysed the role of the reserve margin in power systems with a high penetration of renewable energy. Empirical results have been calculated using aggregated data of 14 WF in the US.

One of the most recent papers on the present subject was published by Li and Park in [22]. In this paper the optimal bidding in the DAM and the RTM (real time market) are calculated. The authors have considered different variables with uncertainties: RTM wind power generation, DAM locational marginal prices (LMPs) (the paper used real data in the PJM market in the U.S. where each node of the system have different prices depending on the state of the system and other variables), RTM LMPs and deviation penalty rates (a single-price deviation is considered in the analysis and this price is the same for every hour in the same day). Two PDF have been used in this work: (i) the PDF of historical actual wind power generation, and (ii) the PDF of wind power prediction errors. This variable has been modelled by the beta distribution function to represent RTM wind power generation distribution. The authors concluded that when using the PDF of wind power prediction errors, they obtain a 6.7% more revenue compared with the obtained when use the PDF of historical actual wind power generation and 3.7% when used the PDF of wind power generation prediction errors compared with bidding the forecasted wind power generation.

The work presented in the present paper advances the current state of the art by introducing an approach based on the analysis of actual energy production forecasts, which enables identifying the associated uncertainty thorough the PDFs and establishing a method for the analytical optimization of the WF's expected income. According to the knowledge of the authors, this work would be the first to propose an analytical approach which considers the daily market price and four deviation prices, whose dependence has been modelled according to a new variable that takes into account the system deviation. This formulation allows a realistic approach to obtain the optimal bidding strategy under the existing market structure in the Iberian system (Spain and Portugal).

Another important point is that the performed analysis demonstrates that the optimal offer is strongly influenced by the deviation of the system, which as mentioned above, is explicitly introduced for the first time in the formulation presented in this paper.

The method proposed in this work also introduces a real practical advantage for WFOs (both in the case of planned plants as well as in the case of plants already in operation), since it is based on the analysis of data that are fully accessible for the WFOs themselves, such as energy production forecasts (usually provided by weather forecasting companies), as well as actual production data. This means that the WFOs can increase its income from energy market participation without the need to incur additional costs or expenses. Therefore, the proposed paper presents an important advantage over those previously stated as it is based on information readily available to the WFOs.

After this brief introduction, the paper is organized as follows. Section II provides a general overview of the proposed approach. Section III presents the problem formulation. The test cases and results are presented in Section IV and conclusions are discussed in Section V.

2. Methodology overview

WFOs are paid for the energy produced at a variable price according to the spot market in case of merchant projects or most commonly at fixed price either by a public support scheme or through a corporate Power Purchase Agreement (PPA). There are different types of PPAs that are out of the scope of this paper, the authors would like to refer to references [23,24] for further details on this topic.

Taking into account the maturity of the wind technology, it is increasingly common that the incentives and support schemes are reduced or even totally eliminated in places with high penetration of variable renewable generation. This is leading to the increasing trend of wind projects to sign a PPAs or to participate in the DAM. In other words, this is leading to an increasing integration of renewable technologies into the markets at a global scale.

The WFO must consider different variables in order to calculate the energy bid for the DAM. In a first stage of the problem, the WFO knows the energy forecast. Making a bid with exactly this value is the approach most commonly adopted by WFO, but this may entail some penalties due to forecast uncertainty.

The methodology proposed in this paper takes into consideration a realistic approach based on identifying the uncertainty related to energy forecasts. To this end, it is proposed to identify the probability density functions (PDFs) of the WF actual production for a given energy production forecast (corresponding to a certain lead time). This identification of the PDFs is carried out by analysing the forecast historical data during a previous training period. This work has been developed using hourly wind production forecasts based on meteorological models, provided by a specialized company in wind energy forecasting to the WFO of an actual Spanish WF. As shown in Figure 1, the aforementioned PDFs are inputs to the module for calculating the expected income function, along with additional input data including the energy production forecast for the hour under analysis, the DAM price, the system deviation (i.e., if the electrical system has surplus or deficit of generation) as well as the deviation costs that are calculated according to Spanish regulations, as explained below in Section III.A.

All these inputs are used to determine the expected income function (explained below in Section III) that subsequently allows the identification of the optimal energy bidding amount (assuming, as it happens in most energy markets, that WFs are price-takers, i.e., their bids are made at zero price) by an analytical optimization approach. The process described in Figure 1 is repeated sequentially for each delivery period (usually 1 hour in the Iberian market, as in most European markets). Thus, for each hour and a given lead time, the first step of the proposed approach is to determine analytically (as detailed later in Section 3) the optimal value of the cumulative probability function for which the expected income is maximized as a function of the DAM and BS prices as well as the system deviation. Once this optimal value of the cumulative probability function is determined, the next step is the numerical identification through the PDF of the value corresponding to the optimal bid energy.

Additionally, it is important to note that the proposed procedure can be applied indistinctly for different time frames, depending on the lead times provided by the forecasting companies, and for any different session of the market (i. e. DAM or IM, etc.).

Finally, it is worth mentioning that the method proposed in this paper focuses on the development of a new approach which is intended to be the core of a complete integrated optimization bidding tool including also the forecast of DAM and BS prices. This work introduces a novel approach to the analytical calculation of the optimal bidding strategy based on the DAM price plus the four BSs prices depending on the system deviation and the historical behaviour of energy forecasts made on the actual production of WFs. Therefore, forecasts about market prices and the behaviour of system deviations are beyond the scope of this paper. In this way, it is possible to analyse the improvement potential of the proposed algorithm and the effect of energy production uncertainty (information which is fully available to WFOs) on the optimal bidding strategy.

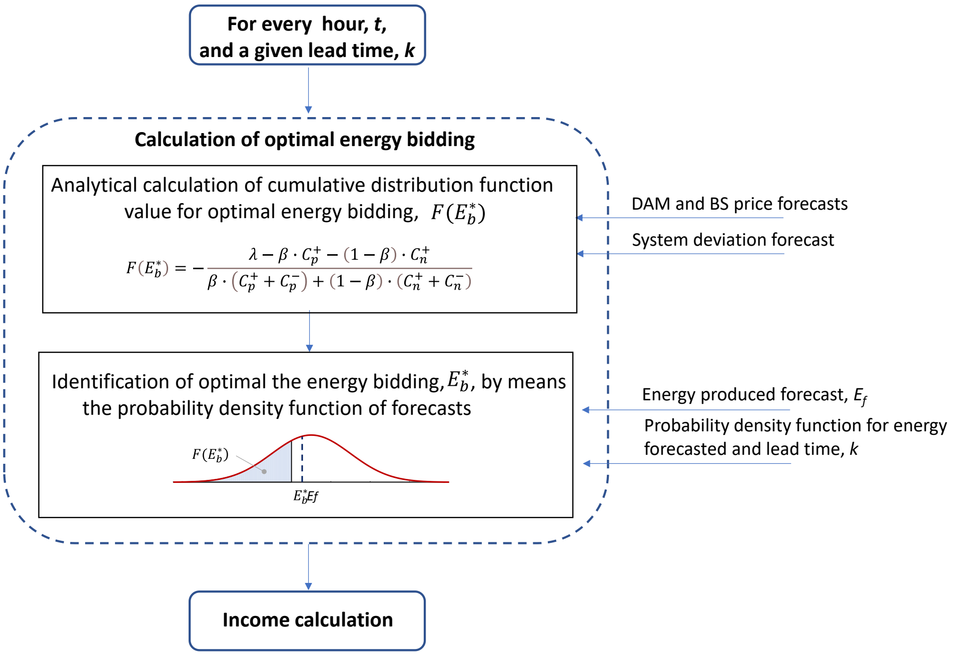

Figure 1. Flowchart of the proposed approach

3. Problem Formulation

At certain instant, t_o, the WFO needs to make a bid in the DAM for the hour t. In order to do this, the WFO receives a production forecast, $E_f(t)$, with a certain lead time, k = *t-to*, (please, note that for the sake of simplicity the lead time has not been included in the nomenclature of the following formulation). However, for the hour t, the WF will eventually generate an energy output $E_p(t)$. Therefore, depending on the energy bid, $E_b(t)$, and the actual energy output for hour *t*, the WFO will have more or less penalties/incomes for the deviations. Therefore, the aim of the method presented on this paper is to maximize the total income from the participation in both the DAM and the BSs.

With this aim, the probability of producing an energy output, E_p, greater than or equal to the bidding energy, E_b, is described in (1) or, otherwise, in (2).

$$1 - F(E_b) = \int_{E_b}^{\infty} f(E_p) dE_p = prob(E_p \geq E_b) \tag{1}$$

$$F(E_b) = \int_{-\infty}^{E_b} f(E_p) dE_p = prob(E_p \leq E_b) \tag{2}$$

where $f(E_b)$ is the probability of producing an energy output E_b.

The expected income, *B*, for a certain scheduling period, *t*, can be described by (3).

$$\begin{aligned} B(E_b) = \lambda \cdot E_b + \beta \cdot C_p^+ \int_{E_b}^{\infty} (E_p - E_b) \cdot f(E_p) \cdot dE_p + \\ \beta \cdot C_p^- \int_{-\infty}^{E_b} (E_b - E_p) \cdot f(E_p) \cdot dE_p + \\ (1-\beta) \cdot C_n^+ \int_{E_b}^{\infty} (E_p - E_b) \cdot f(E_p) \cdot dE_p + \end{aligned} \tag{3}$$

$$(1-\beta)\cdot C_n^- \int_{-\infty}^{E_b} (E_b - E_p)\cdot f(E_p)\cdot dE_p$$

where λ is the marginal price of the day ahead market, C_p^+ is the cost of a positive deviation of the WF output (in case there is a generation surplus with respect to the energy bidden in the DAM) being positive the deviation of the system (in case the overall energy generation in the system is actually higher than the scheduled), C_p^- is the cost of a negative deviation being positive the deviation of the system, C_n^+ is the cost of a positive deviation being negative the deviation of the system, C_n^- is the cost of a negative deviation being negative the deviation of the system, β is the probability of the system's deviation being positive, and then $(1-\beta)$ is the probability of the system´s deviation being negative. It is worth noting that this new formulation, introduced in this work, of the expected income by considering the four existing prices in the BSs and depending on the probability of deviation of the system, allows modelling in a completely realistic way the problem of optimal supply by the wind farms participating in the Spanish electricity system, according to the scheme of operation of the DAM and the BSs in the Iberian electricity market.

It is important to note that all the formulation in the paper is referred to as costs to the system/market, being equivalent to the selling price for the energy produced by the plant. In order to find the maximum expected income, equation (3) is derived as a function of the energy bided:

$$\frac{\partial B(E_b)}{\partial E_b} = \lambda + \beta\cdot C_p^+\left[-\int_{E_b}^{\infty} f(E_p)\cdot dE_p\right] + \beta\cdot C_p^-\left[\int_{-\infty}^{E_b} f(E_p)\cdot dE_p\right] +$$
$$+(1-\beta)\cdot C_n^+\left[-\int_{E_b}^{\infty} f(E_p)\cdot dE_p\right] + (1-\beta)\cdot C_n^-\left[\int_{-\infty}^{E_b} f(E_p)\cdot dE_p\right] \qquad (4)$$

Substituting (1) and (2) in (4):

$$\frac{\partial B(E_b)}{\partial E_b} = \lambda + \beta\cdot C_p^+[F(E_b)-1] + \beta\cdot C_p^-\cdot F(E_b) +$$
$$+(1-\beta)\cdot C_n^+[F(E_b)-1] + (1-\beta)\cdot C_n^-\cdot F(E_b) \qquad (5)$$

It is possible to obtain the value of $F(E_b)$ which makes null (5).

$$F(E_b^*) = -\frac{\lambda - \beta\cdot C_p^+ - (1-\beta)\cdot C_n^+}{\beta\cdot(C_p^+ + C_p^-) + (1-\beta)\cdot(C_n^+ + C_n^-)} \qquad (6)$$

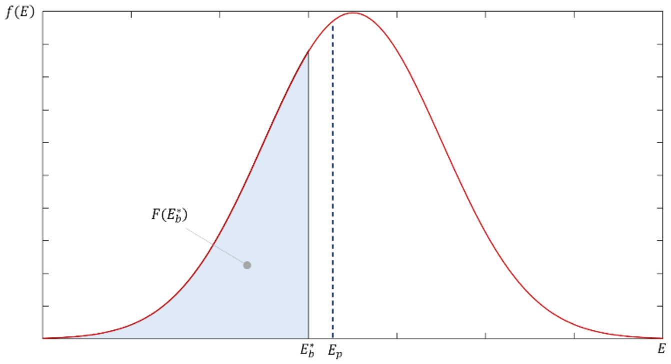

Figure 2. Schematic representation of the optimal energy bidding depending on the probability density function.

where E_b^* is the optimal energy bid. Once the optimum value of $F(E_b)$ has been calculated using (6), it is possible to determine the value of E_b^*, taking into account the PDF of actual energy produced for a given energy forecast, as shown in Figure 2. The value $F(E_b^*)$, obtained through (6) represents the cumulative distribution function for E_b^*. In graphic terms, this represents the area filled in blue colour in Figure 2, therefore once the value of $F(E_b^*)$ is determined and the PDF is known it is possible to determine the value of the optimal bid E_b^*.

It is worth noting several dependencies and conditions that the variables of equation (6) comply:

- $C_n^+, C_p^+ \geq 0$; Generators do not pay for the energy yield to the system (even if the system has excess of generation).
- $C_n^+ = \lambda$; The deviation benefits the system and the generator get paid at marginal price.
- $C_p^+ \leq \lambda$; The deviation does not benefit the system and the generator gets paid at a price smaller than the DAM price.
- $C_n^-, C_p^- \leq 0$; The plant generates less than the energy bidden, consequently it must pay to the system.
- $C_p^- = -\lambda$; The deviation benefits the system and the generator must pay the deviation at marginal price (in such a way the plant gets paid exactly the energy delivered to the system without costs and benefits).
- $|C_n^-| \geq \lambda$; The plant pays for the shortfall in the energy delivered to the system at a price higher than the marginal market price.

In case the negative deviation benefits the system (i.e., if there is generation surplus in the system), the plant just will be paid for the energy generated (as a result of the energy bidden minus the deviation) at marginal price. If the deviation is negative and is unfavourable to the system (due to an overall lack of generation), the generator will be penalized with an extra payment, being the total cost (negative too) greater than the marginal price of the system. On the other hand, positive deviation costs will be greater or equal to cero. In case that the deviation benefits the system, the generator will be paid for the energy generated (energy bidden plus the deviation) at marginal price. On the contrary, if the deviation is unfavourable to the system, the generator will be paid for the excess of energy at a price smaller that the marginal price.

The value of $F(E_b^*)$ stated in (6) corresponds with a maximum of the expected income. The demonstration is shown in the lines by calculating the second derivative of the expected income function:

$$
\begin{gathered}
\frac{\partial^2 B(E_b)}{\partial E_b^2} = \frac{\partial}{\partial E_b}\left[\beta \cdot C_p^+ \cdot (F(E_b) - 1)\right] + \frac{\partial}{\partial E_b}\left[\beta \cdot C_p^- \cdot F(E_b)\right] + \\
+\frac{\partial}{\partial E_b}[(1-\beta) \cdot C_n^+ \cdot (F(E_b) - 1)] + \frac{\partial}{\partial E_b}[(1-\beta) \cdot C_n^- \cdot F(E_b)] = \\
\beta \cdot C_p^+ \cdot \frac{\partial}{\partial E_b}[F(E_b)] + \beta \cdot C_p^- \cdot \frac{\partial}{\partial E_b}[F(E_b)] + (1-\beta) \cdot C_n^+ \cdot \frac{\partial}{\partial E_b}[F(E_b)] + (1-\beta) \cdot C_n^- \cdot \frac{\partial}{\partial E_b}[F(E_b)] = \beta \cdot C_p^+ \cdot \\
f(E_b) + \beta \cdot C_p^- \cdot f(E_b) + \\
+(1-\beta) \cdot C_n^+ \cdot f(E_b) + (1-\beta) \cdot C_n^- \cdot f(E_b) = \\
f(E_b) \cdot \left[\beta \cdot \left(C_p^+ + C_p^-\right) + (1-\beta) \cdot (C_n^+ + C_n^-)\right]
\end{gathered}
\tag{7}
$$

Taking into account the aforementioned relationships among costs, the relations (8) and (9) can be easily deduced.

$$C_p^+ + C_p^- \leq 0 \tag{8}$$

$$C_n^+ + C_n^- \leq 0 \tag{9}$$

Considering also that β and $f(E_b)$ only can take values within the range [0,1], they both represent probabilities. It can be demonstrated that the second derivative of the expected income function is negative for all values of E_b, and consequently it will be for the optimal bidding energy volume, E_b^*, obtained by (6). Therefore, this optimal bid corresponds with a maximum in the income function.

3.1 Calculation of deviation costs in the Iberian market

This section presents an overview of the calculation of the deviation costs for the Iberian market [25]. These costs are used to calculate the value of $F(E_b^*)$, according to (6). All data used to make the costs calculations have been retrieved from the Spanish Transmission System Operator, REE, [26].

With the aim of calculating the deviation costs, it is important to know the hourly net balance of assigned energy as well upward and downward NBEUD). This variable stands for the generation needs of the system, so that if its value is negative the system has surplus of generation and, otherwise, if its value is no negative the system has a shortage of generation.

$$\begin{aligned} NBEUD = & \sum_{u,s} \left(AEIMU_{u,s} + AEIMD_{u,s}\right) \\ & + \sum_{u} \left(AETERU_u + AETERD_u\right) + \sum_{z} \left(AESECU_z + AESECD_z\right) \\ & + \sum_{i,b} \left(EIIB_{i,b} + EEIB_{i,b}\right) \end{aligned} \tag{10}$$

where:

- $AEIMU_{u,s}$ and $AEIMD_{u,s}$ are the assigned energy upward and downward, respectively, by the imbalance management procedure of the unit *u* in session *s*.
- $AETERU_u$ and $AETERD_u$ are the assigned energy by tertiary reserve upward and downward of the unit *u*, respectively.
- $AESECU_z$ and $AESECD_z$ are the assigned energy by secondary reserve upward and downward of the regulation zone *z*, respectively.
- $EIIB_{i,b}$ and $EEIB_{i,b}$ are energy imported and exported, respectively, in the bid block *b* corresponding to the interconnection balance for the interconnection *i*.

3.1.1 *Costs of upward deviation by the wind farm*

If the system has a generation surplus, the hourly price of the WF deviation upward, C_p^+, is calculated as (11).

$$C_p^+ = \min(MPDAM, WAPU) \tag{11}$$

where $MPDAM$ is the marginal price of the day ahead market, and $WAPU$ is the weighted average price of the energies upward on the imbalance management, secondary reserve, and tertiary reserve.

If the deviation of the system is downward, the upward WF deviation, C_n^+, is calculated as follows:

$$C_n^+ = MPDAM \tag{12}$$

3.1.2 *Costs of downward deviation by the wind farm*

If the system has a generation deficit, the hourly price of the wind farm deviation downward, C_n^-, is calculated as (13).

$$C_n^- = \max(MPDAM, WAPD) \tag{13}$$

where $WAPD$ is the weighted average price of the energies downward on the imbalance management, secondary reserve, and tertiary reserve.

If the deviation of the system is upward, the downward WF deviation, C_p^-, is calculated as follows:

$$C_p^- = MPDAM \tag{14}$$

3.2 Calculation of the probability density function

As shown above, the result of (6) is the cumulated distribution function which makes possible the calculation of the optimal energy bidden. This value can be calculated by knowing the PDF of a determined WF. The PDF represents the probability of producing a certain value of energy, E, having forecasted an E_f in advance of k hours.

Table 1. Wind Farm actual production and forecast structure.

Hour	**Energy Production**	**E Forecasted 1**	**E Forecasted 2**	**….**	**E Forecasted k-1**	**E Forecasted k**
1	*E1*	*E1,1*	*E1,2*	...	*E1,k-1*	*E1,k*
2	*E2*	*E2,1*	*E2,2*	...	*E2,k-1*	*E2,k*
….	...	...	...	...	...	...
n-1	*En-1*	*En-1,1*	*En-1,2*	...	*En-1,k-1*	*En-1,k*
n	*En*	*En,1*	*En,2*	...	*En,k-1*	*En,k*

In this work, the PDF has been estimated by using real data for half a year of an actual operating WF in Spain, as previously mentioned. The raw data is composed of the real hourly production of the WF and the energy forecasted for every hour of the analysed period with lead times, *k*, varying from 1 hour to 36 hours. In this way, data are organized according to the structure shown Table 1. In that table, Eh refers to the actual energy production for the hour *h*, while $E_{t,k}$ refers to the energy production for hour *t*, forecasted *k* hours in advance. Taking into consideration these data, it is possible to determine the probability of producing each value of energy output having forecasted a certain energy production.

The first step to obtain the PDFs for a given lead time, *k*, is to discretize the possible generation values of the WF in a number of predefined intervals. After this, per each of the intervals of energy, the occurrences of the values of actually generated energy are identified, considering the same discretization interval. The last step is to approximate the PDF for each energy forecasted interval by the histogram, which is obtained by dividing the occurrence of each interval of generated energy by the total number of samples corresponding to this forecasted energy interval. The process is summarized in the flowchart of Figure 3. This approach allows to find the PDF in a systematic way and from real data always available for all wind farm operators.

The WF under study has a rated power of 28 MW. A discretization interval of 1 MWh has been considered for both energy values generated and forecasted, so that the PDF for a given lead time is approximated by matrix of 28 x 28 elements. As shown later in the data provided in Annex A, in this matrix, each row represents each interval of energy forecasted. In the same way, each column represents the probability (in percentage) of generating the corresponding energy value having forecasted (for a given lead time) the energy value corresponding to each row.

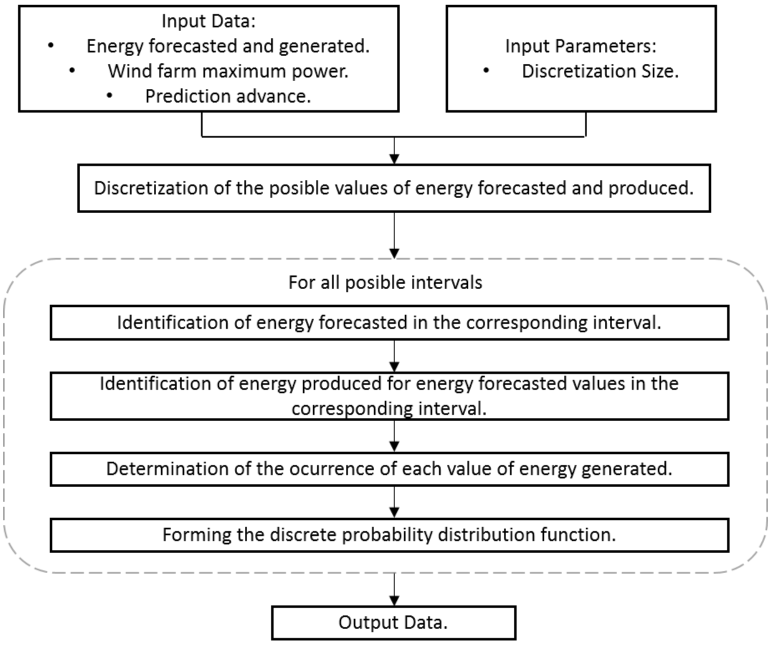

Figure 3. Flowchart of the calculation module for the probability density function of actual energy produced for a given energy forecast.

4. Test Cases

As previously mentioned, the methodology proposed in this paper has been tested in two test cases based on real hourly production data from an actual 28 MW WF located in Spain, as well as the production forecasts provided for lead times from 1 h to 36 h, since the present study is based on the Iberian electricity market in which the energy of the 24 hours of the following day (D+1) are traded at noon of the present day (D). These real data correspond to the whole year 2016. The data collected during the first half of the year have been used to calculate the histograms that approximate the PDF according to the procedure introduced in Section 3.2. The Annex provides the data corresponding to the histogram obtained for a lead time of 24 h.

On the other hand, the data corresponding to the second half of 2016 have been used to validate the proposed methodology. However, for simplicity in providing all the data corresponding to the six months of validation, the following figures 4 to 10 show in detail the data corresponding to the first two weeks of the second half of 2016 (i.e. from the hour 4381 onwards). All calculations have been programmed on MATLAB R2016b and calculated using an Intel(R) Core(TM) i3 CPU M380 @ 2.53 GHz 2.53 GHz.

4.1 Case 1

As mentioned above, the DAM prices and the BS prices are available in [26]. Figure 4 shows the evolution of the DAM price and BS. The lower part of Figure 4 also shows the system deviation for each hour, the black bars represent the hours for which the system deviation is positive (i.e., β =1). On the contrary, the white bars stand for the hours in which the system's deviation is negative (i.e., β =0).

Figure 5 shows the WF actual hourly production together with the values of the forecasts corresponding to a 24-hour lead time.

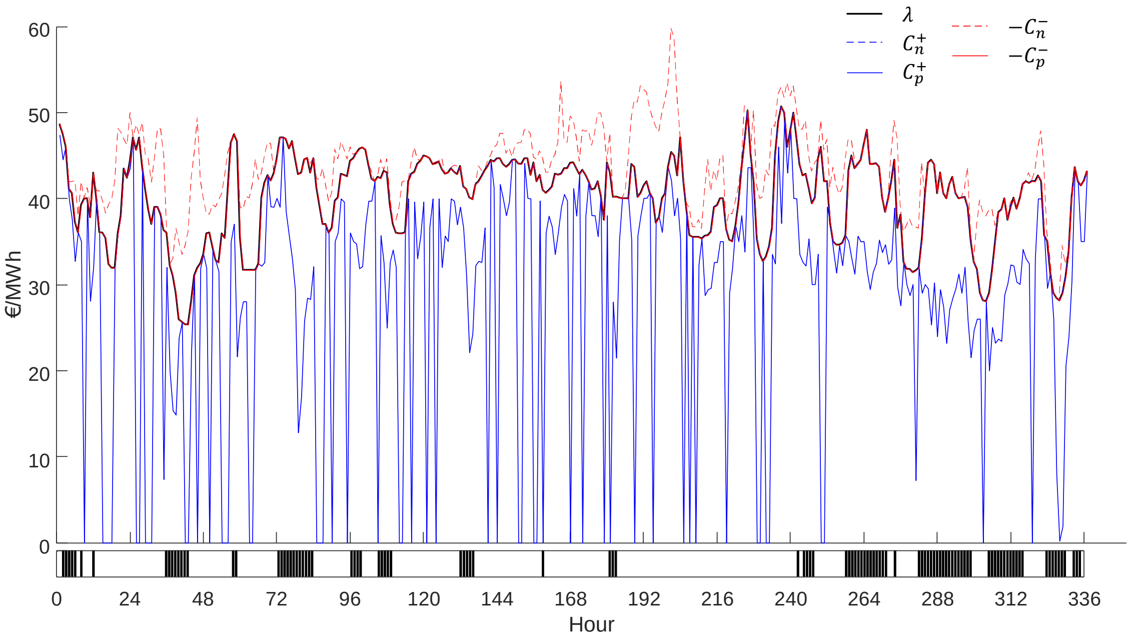

Figure 4. Evolution of the hourly prices of the DAM and hourly balancing prices for the first two weeks of the analysed period.

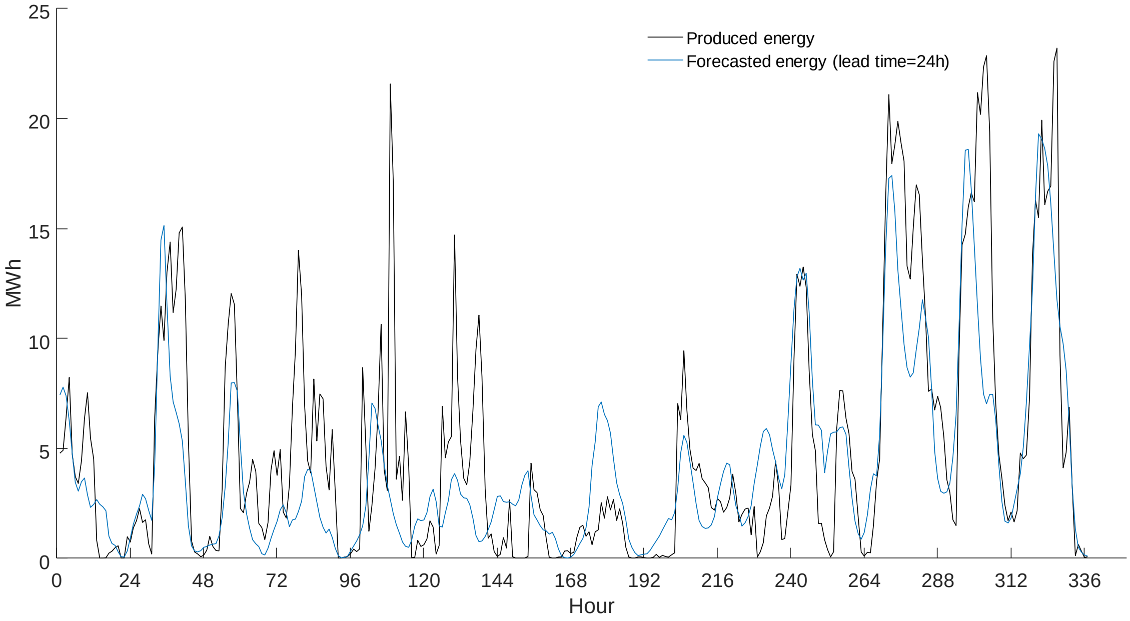

Figure 5. Evolution of actual produced energy and forecast for the first two weeks the analysed period.

Table 2. Income (€) obtained by the WF for the analysed approaches for Case 1 and Case 2.

	Case 1		Case 2	
	Two-weeks period	Second half 2016	Two-weeks period	Second half 2016

Conventional approach	59788	883786	44735	689821
Proposed approach	63797	927158	56105	813252
Theoretical maximum	63797	927158	63797	927158

Figure 6 shows the hourly income obtained through the proposed methodology and through the conventional approach based on bidding the forecasted energy. As can be seen in Table 2, the proposed methodology improves the income in comparison to the conventional approach. The total income using the proposed methodology during the first two weeks of the period under study would be 63797€, while by using the conventional approach the income would be 59788 €. This means a 6.7% of improvement obtained by the proposed strategy. Extending the period of analysis to the whole second half of 2016, the total income achieved through the proposed approach would be 927158 €, whereby the conventional approach would obtain 883786 €, which is a 4.9% of improvement. Figure 6 also shows the theoretical maximum income (represented by the blue circles) that would be possible to achieve if the energy forecasts were perfect (i.e., under this approach the bids are exactly the actual generated energy, represented by the black line in Figure 5). It is interesting to note that the proposed strategy achieves the theoretical maximum possible for all hours in the entire period analysed (the second half of 2016). These results show the great potential of the proposed method to maximize the WF income. The proposed strategy achieves the theoretical maximum and simplifies, for the Spanish case, the variables to be taken into account to make the bid, reducing it only to the system's deviation. This is due to the price structure of BS in the Spanish system, which, as detailed in the following lines, leads to the optimal supply to be independent of the energy forecast, as well as of market prices; depending only on whether the entire system has a deficit or surplus of generation.

Additionally, it can also be seen how in some hours the income obtained through the conventional approach is negative, this situation occurs mainly in those cases where the plant bided a certain energy in the DAM, but eventually the real production of the plant was lower than forecasted or even zero.

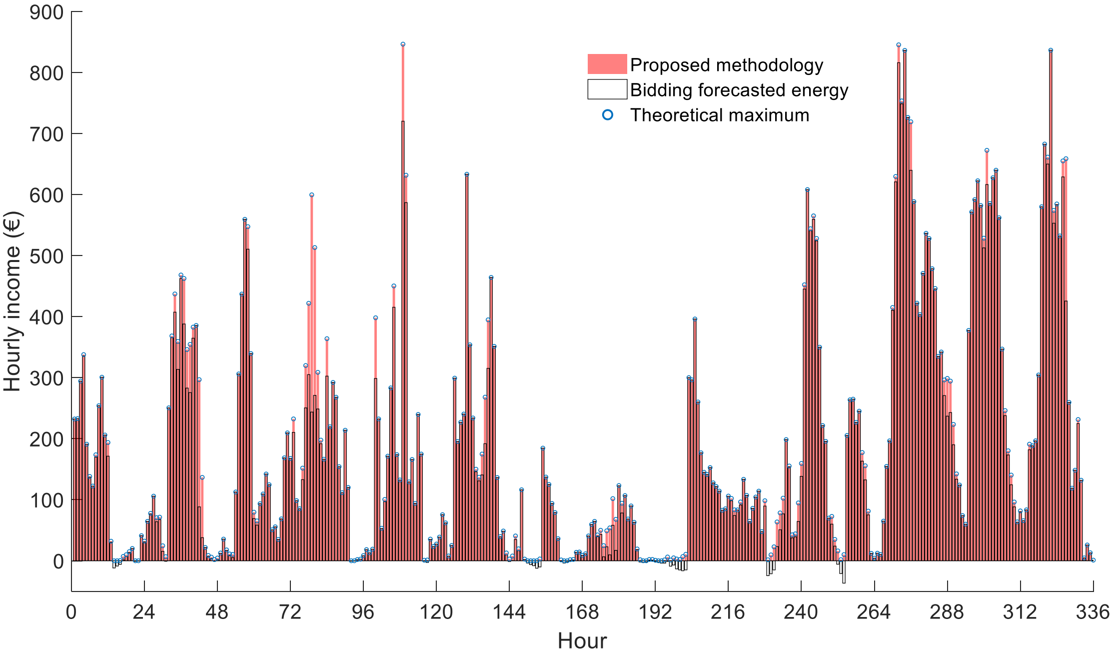

Figure 6. Comparison of hourly income between the proposed approach and the conventional approach

consisting on bidding the forecasted energy for Case 1.

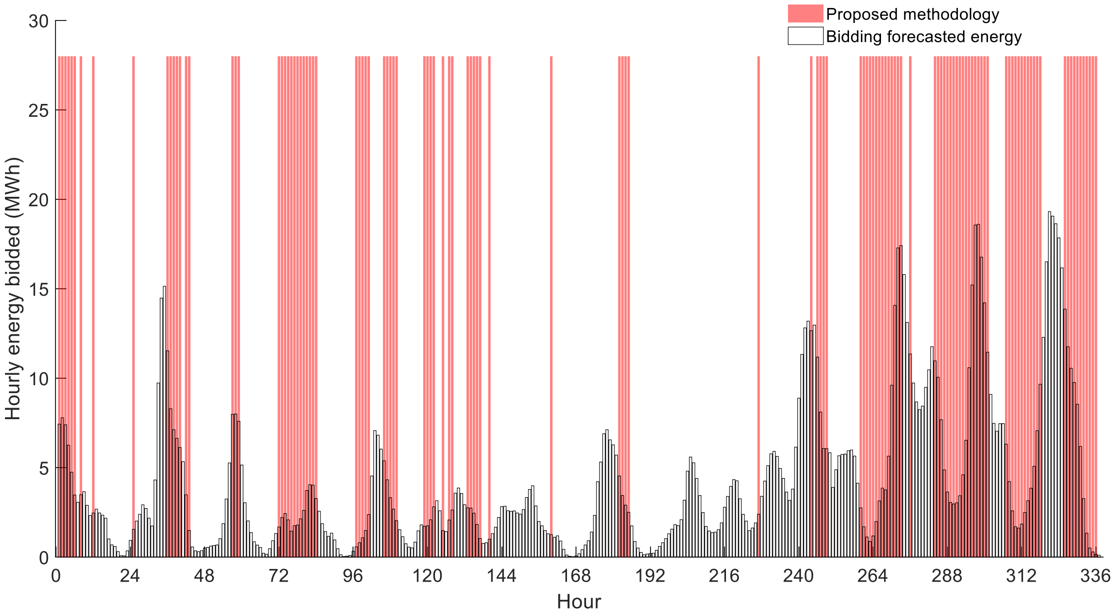

Figure 7. Comparison of hourly bidding strategies between the proposed approach and the conventional approach consisting on bidding the forecasted energy for Case 1.

Figure 7 shows a comparison between the bids made by the two approaches analysed. As can be seen, the conventional approach consists simply of bidding the available forecasted energy for the corresponding lead time (in this case 24 h), whereas the bids made using the proposed approach consist of bidding either zero energy or energy equal to the plant's nominal power. This is a consequence of the price structure of the DAM and the BS in Spain. As can be seen in Figure 4, in the Spanish markets, the equality $\lambda = -C_p^-$ is true for every hour. This means that when the system deviation is positive (i.e., $\beta = 1$) the value of $F(E_b^*)$, obtained through equation (6), is equal to 1. The consequence is that in this case the optimal strategy consists in bidding the nominal power of the WF, independently of the PDF of the energy forecasts and of the levels reached by the prices of DAM and BS. In the same way, the following relationship is also fulfilled for all hours in the Spanish market: $\lambda = C_n^+$, this implies that for all hours when the system deviation is negative (i.e., $\beta = 0$), the value of $F(E_b^*)$ is null, which makes the optimal bid in this case to be also null.

In summary, with the current price structure in the Spanish markets it is possible to establish an optimal strategy based only on predicting the behaviour of the system deviation and bidding zero energy (or, in practical terms, the minimum allowed volume to be entitled to participate in the DAM and BS according to the Iberian market regulation) in the case of a negative system deviation or the maximum energy of the plant in the case of a positive system deviation. This is because the price formation of the BS in the Iberian/Spanish market does not always penalize generators (including renewable plants) for their deviations. Spanish market rules only penalize generators when their deviations are contrary to the system. When the deviations are favourable to the system, even though the actual production of the generator differs (in excess or defect) from the energy committed for that hour, the generator is not penalized for its deviation. This could have important consequences from the point of view of energy policies, because in the transition towards a highly decarbonized system, with high penetration of variable technologies, it could be convenient that every market agent were fully responsible for the deviations produced over their committed generation or demand. Renewable generator could be especially concerned with this new regulation approach, since when their actual productions did not exactly match the scheduled amounts, they would result penalized, even when their deviations were favourable to the system.

4.1.1 Sensitivity analysis

The objective of this sensitivity study is to analyse in a more realistic way the real applicability of the proposed approach to obtain the optimal bid for a wind farm. To this end, instead of considering the prices of the DAM and BS as previously known at the time of making the bid, the uncertainty of the forecast of these prices has been modelled by adding a random noise by means a normal variable (it should be noted, however, that the relationships between the different prices currently in force in the Spanish markets, i.e., $\lambda = -C_p^-$ and $\lambda = C_n^+$ as mentioned above, have also been taken into account in this sensitivity analysis), which allows emulating the behaviour of the estimates provided by the prices forecasting algorithms. Likewise, the existing uncertainty in the forecast of the electricity system deviation has also been modelled by adding an error probability on this variable for every hour of the studied period. In this way, the sensitivity analysis proposed in this section consists of analysing the percentage improvement obtained by the proposed methodology compared to the classical approach consisting of bidding the forecasted energy.

Figure 8 shows the results obtained in the sensitivity analysis performed for this case, varying the error in predicting the deviation of the system in the range 1%-10%. The results obtained correspond to the average values obtained after 10 executions of the proposed algorithm (thus mitigating the random component in the presentation of results) during the entire period analysed in this Case 1 (i.e., the second half of 2016). Furthermore, this analysis has been reproduced also considering the error in the prices of the DAM and the BS, varying within the range of 2%-10%. As can be seen, the results obtained are not affected by the error introduced in the prices. This is due to the fact that in this case the relations between the prices of the DAM and the existing BS in the Iberian market are fulfilled, which leads to that, as explained above, the optimal bid is independent of the prices and only depends on the direction of the deviation of the system. On the other hand, it can also be noted, the virtually linear dependence of the percentage of improvement depending on the error introduced in the deviation of the system. For low values of the error in the system deviation, the percentage of improvement is similar to that obtained in the ideal situation where the system deviation is assumed to be known beforehand. However, as the system deviation error increases, the percentage of improvement gradually decreases. This figure allows to draw an important conclusion, since the potential of the tool proposed in this work is directly linked to the accuracy of the techniques for predicting the behaviour of the system deviation: assuming that the typical error of the forecast tools is between 5 and 8%, the potential of improvement that would be obtained by means of the approach proposed in this work would be within the range of 1-2.5%, which shows its viability in realistic conditions.

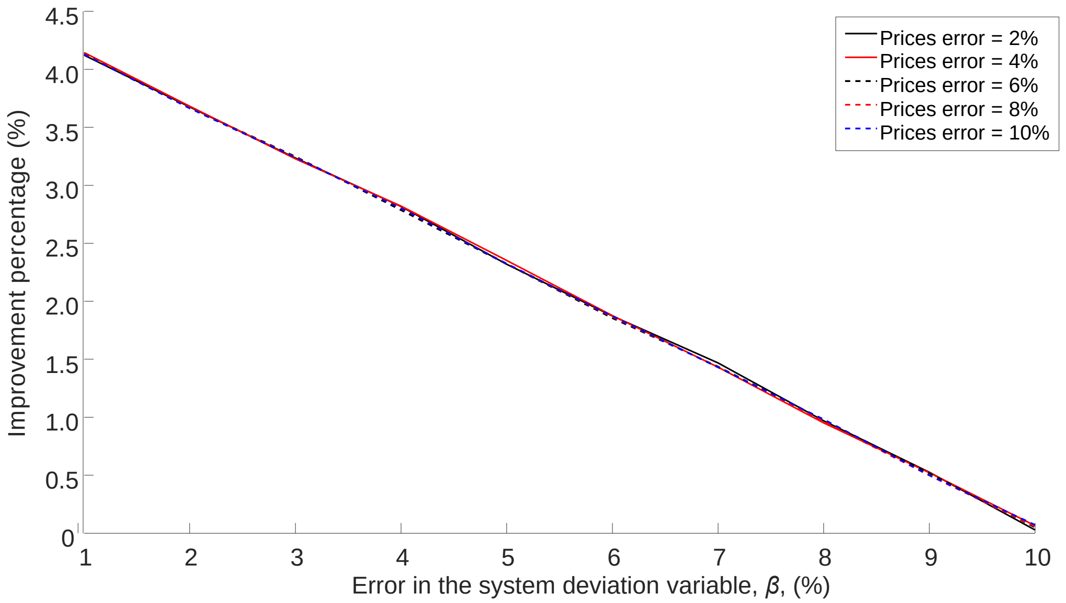

Figure 8. Sensitivity analysis to forecast error in DAM and BSs prices and system deviation for Case1.

4.2 Case 2

In this second test case, an alternative price structure of the BS is proposed so that in all cases deviations of the renewable plant from the scheduled energy are penalized. In this way, the aim is now to analyse an alternative scenario corresponding to a future possible market rules that would penalise any kind of deviation, even when those deviations are favourable to the system. In this case, the following assumptions are proposed to establish the basic rules for the formation of prices corresponding to the BS:

(i) If a power plant has a positive deviation and the system deviation is also positive, the deviation produced by the plant does not benefit the system and therefore the plant will not receive any remuneration for the additional energy injected, apart from the scheduled/dispatched in the DAM, i.e.: $C_p^+ = 0$.

(ii) If the plant has a negative deviation and the system deviation is also negative, the deviation again negatively impacts the system so that the plant will no longer receive the market price for the unsupplied energy and will additionally be responsible for acquiring such energy deficit for the system at the double of the wholesale market price. In this way, $C_n^- = -2\lambda$.

(iii) If the generator deviation is positive and the system has a generation deficit, the system is benefited from the plant deviation, so it is proposed that the plant should receive a price slightly lower than the DAM price, because its deviation introduces a disturbance that should be penalized. In this case, it is proposed that the retribution received is penalized in a linear manner, based on the ratio between the total generation deficit and the total energy of the system in each hour, reaching a maximum penalty of 10% over the DAM price for the maximum value of the aforementioned ratio during the second half of 2016.

(iv) If the power plant deviation is negative and the system has excess generation, the deviation introduced by the plant favours the system again. In this case it is proposed to slightly penalize the plant following an approach completely analogous to the previous assumption.

Based on these rules, the hourly prices of the BS have been obtained as shown in Figure 9.

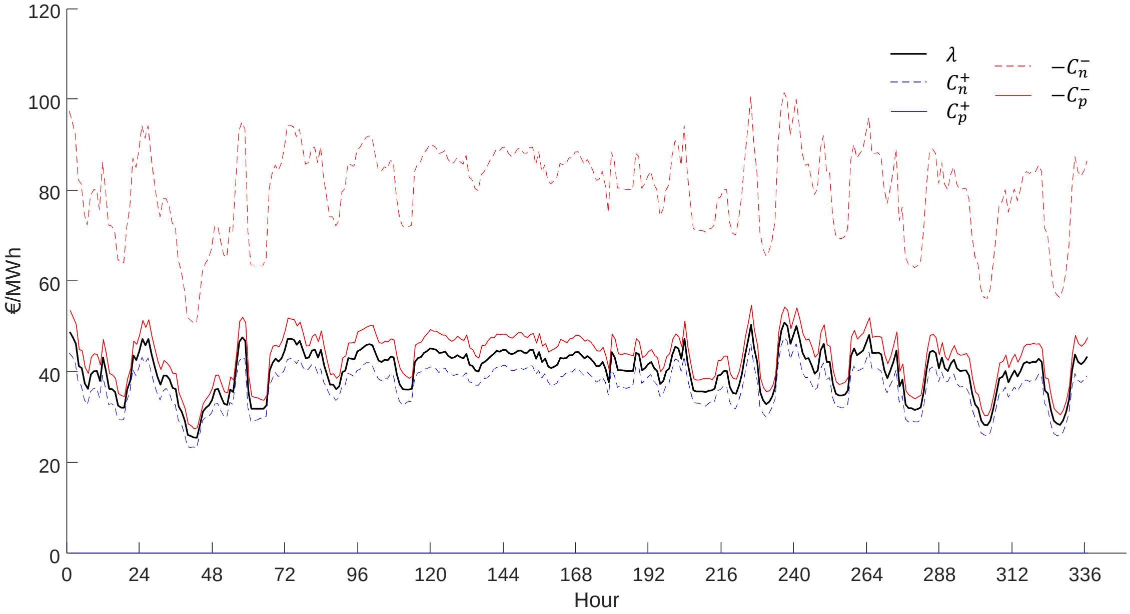

Figure 9. Proposed modified hourly prices of BS for Case 2 for the first two weeks of the analysed period.

Figure 10 shows the comparison between the hourly income obtained through the two proposed approaches. It can be seen how the proposed strategy improves the income obtained for most of the hours of the two weeks under study. It can also be seen how the frequency and severity of negative income increases for certain hours, as a result of the greater penalties introduced in the prices of BS. As it can be inferred from Table 2, the improvement ratio of total revenues obtained through the methodology proposed in this second case is of 26.4% for the first two weeks of the second half of 2016 and 19.6% considering the second complete second half of the year. These values are significantly higher than those of Case 1, due again to the greater penalty of the cost of the deviations for the plant considered in this case. Additionally, the blue dots show the theoretical maximum hourly income if the energy forecasts were perfect (i.e., the forecasts were exactly the same as the energy finally generated). In this case the proposed strategy does not reach the theoretical maximum, since in this situation the prices of the BS lead the bidding strategy to be dependent on the accuracy of the energy forecast. This means that during the first two weeks of the analysed period, the proposed strategy reaches revenues that are 12.1% below the theoretical maximum, while for the entire second half of the year the revenues obtained would be 12.3% lower than the theoretical maximum.

Figure 11 shows the comparison between the bids for each of the hours. In this case, the hourly volume of energy bid using the proposed methodology is usually different from zero or from the plant's rated capacity, because the price structure of the BS considered in Case 2 leads to values of $F(E_b^*)$ different from zero or one, which implies that the expected income function, depending on the energy bid, has a maximum that can take on any value within the range between 0 and the plant's nominal power.

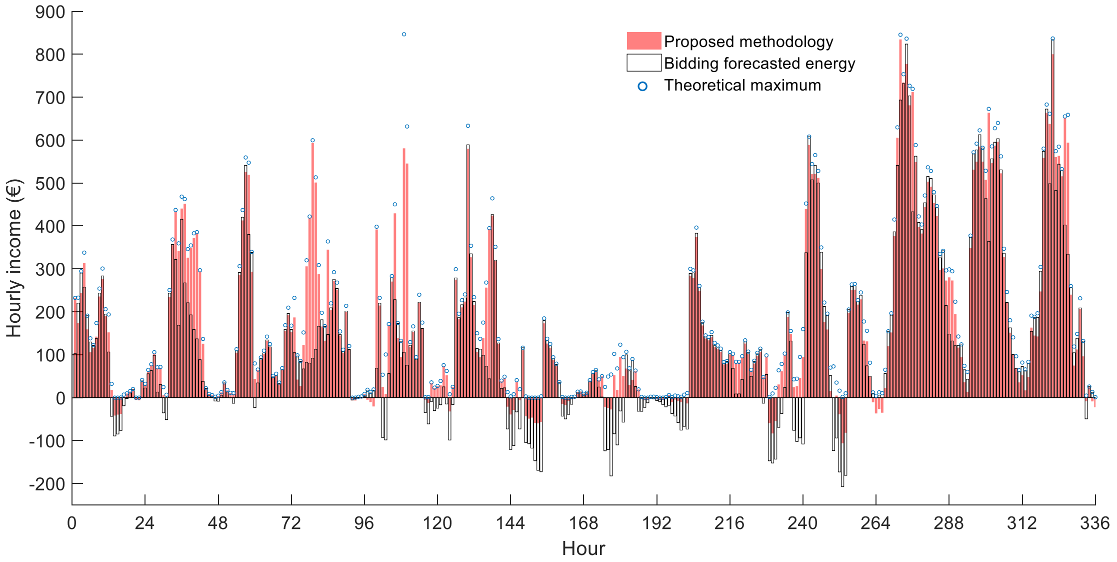

Figure 10. Comparison of hourly income between the proposed approach and the conventional approach consisting on bidding the forecasted energy for Case 2.

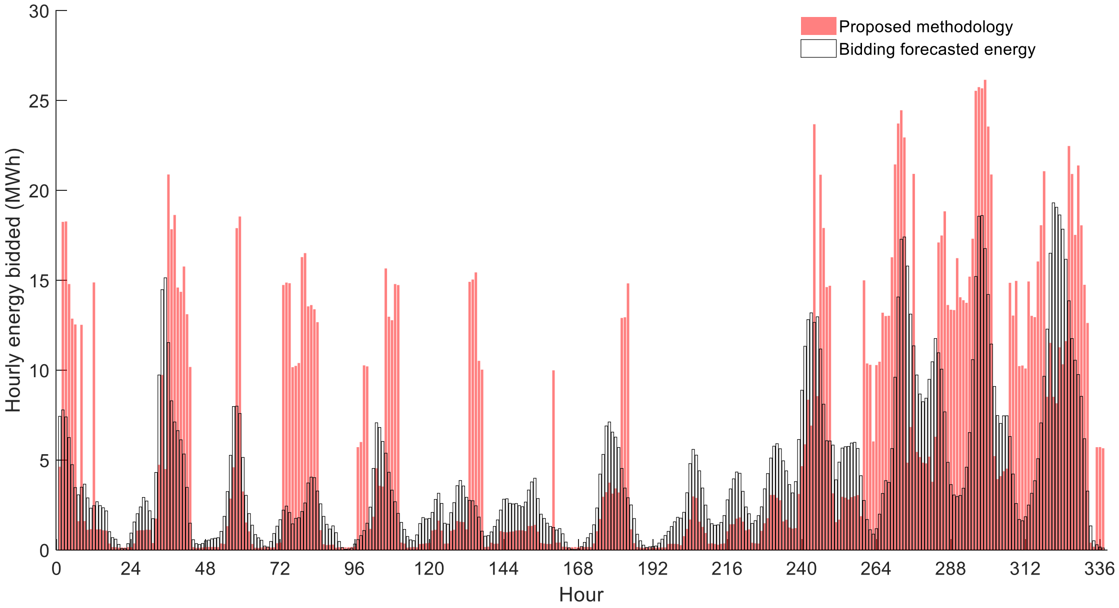

Figure 11. Comparison of hourly bidding strategies between the proposed approach and the conventional approach consisting on bidding the forecasted energy for Case 2.

Finally, Figure 12 shows the improvement ratio obtained between the proposed and conventional approaches for Case 2 depending on the forecast lead time. As it was expected, the proposed methodology obtains a greater improvement as the forecast lead time increases, since the forecasts are more accurate as they are closer to the energy delivery time, which reduces the deviations uncertainty. It should also be noted that the improvement ratio corresponding to the usual lead times for participation in the day ahead market (between 12 and 36 hours) is around 17-18%, which will presumably enable even significant improvement margins to be obtained in the case of implementing a complete optimal bidding tool including also the forecast of prices in the DAM and BS.

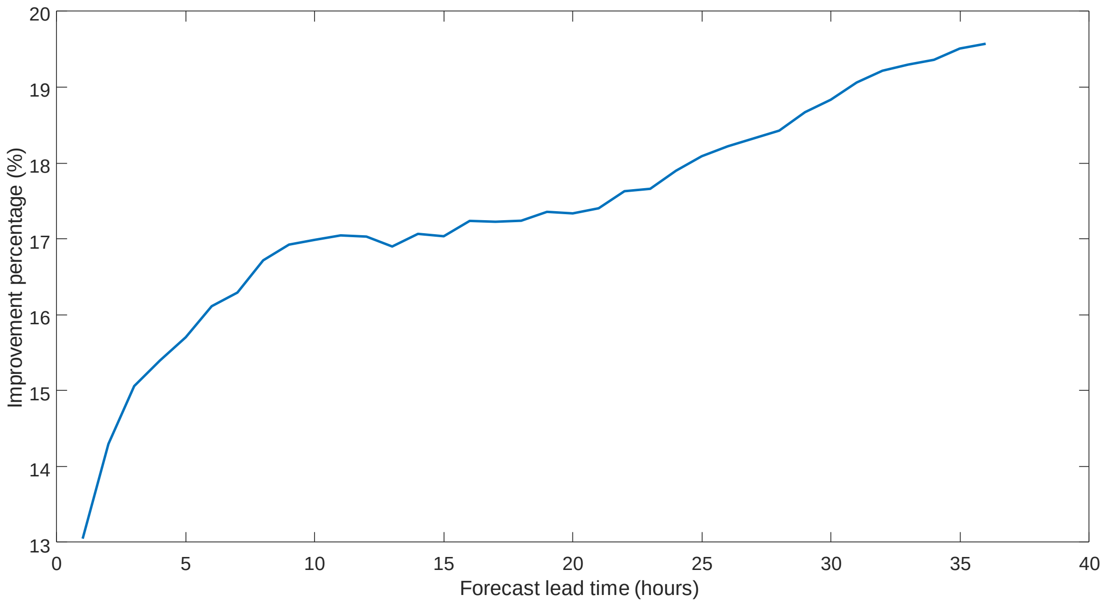

Figure 12. Improvement ratio of the proposed methodology versus the conventional bidding strategy depending on the forecast lead time for Case 2.

4.2.1 Sensitivity analysis

Figure 13 shows the results of the sensitivity analysis performed on Case 2. In this analysis, the relationships mentioned above for this case between the different prices of the DAM and the BS have been considered and subsequently modified by introducing a random error to each of them. Likewise, as in the previous section, an error has also been considered on the variable for estimating the deviation of the electrical system.

As can be seen in the figure, under the considerations introduced in the sensitivity analysis of this second case, the percentage of improvement depends on both the error in estimating the direction of the system deviation, as well as the error considered in the prices of DAM and BS. In a similar way to what happened in Case 1, the dependence of the percentage improvement on the error in the system deviation is almost linear (for the same value of error in the prices of DAM and BS). On the other hand, as the error in the estimation of the prices of DAM and BS increases, the percentage of improvement obtained through the proposed methodology is also progressively reduced. As an example, for a typical error in the estimation of prices and the deviation of the system of about 5-8%, the percentage range of improvement obtained would be about 5-10% (the lower edge corresponding to an error of 8% in the estimation of prices and direction of the deviation, while the upper edge would correspond to an error of 5%), which again highlights the potential of the proposed methodology to a price scenario such as the one proposed in this second test case.

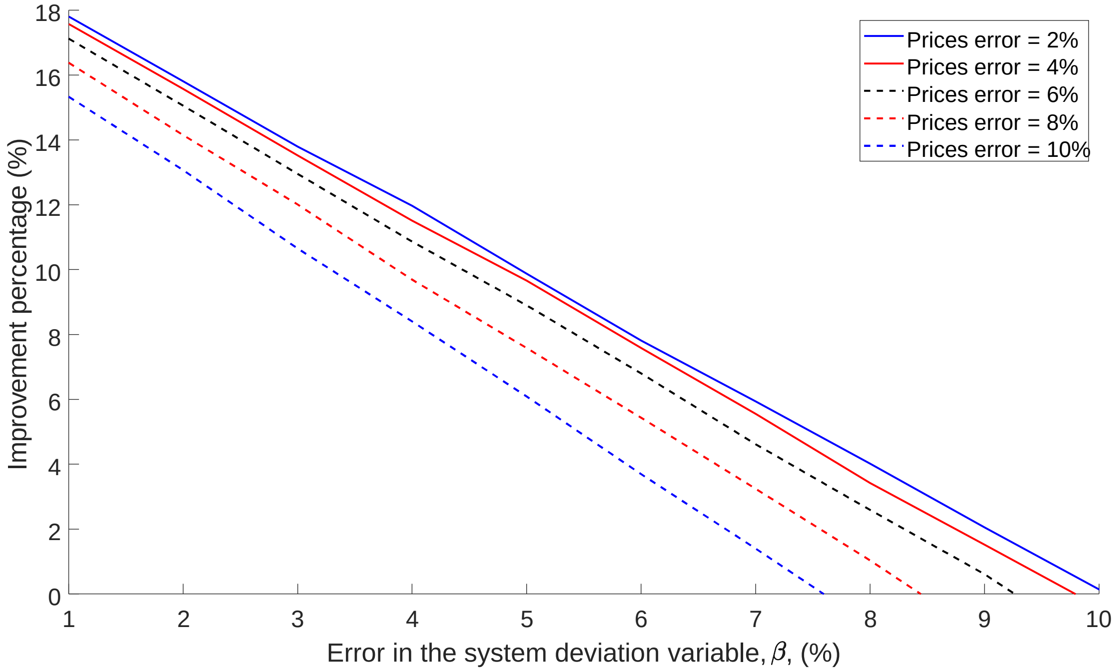

Figure 13. Sensitivity analysis to forecast error in DAM and BSs prices and system deviation for Case2.

4.3 Results discussion

The results shown in these case studies highlight the applicability of the proposed method in a realistic environment. In fact, all the data considered in Case 1 proceeds from a real application, in which both the production data and the forecast data for different lead times correspond to an existing wind farm. Likewise, the remaining variables involved in the problem (i.e., the hourly price of the DAM and the four hourly prices of the BSs, as well as the direction of the system's deviation) have been taken from the actual results provided by the Spanish System Operator. The results of the first case study show that the improvement potential that the proposed methodology would have over the classical approach based on bidding the forecasted energy for the corresponding lead time is around 4.9% for the whole period analysed. However, it is worth mentioning that this first analysis considers that the prices of DAM and BS, as well as the deviation of the system are known beforehand, so it is also essential to analyse the influence of the errors associated with the forecasting techniques of these variables. For this reason, a sensitivity analysis to these errors has also been carried out, showing that for a typical range of error in the forecast of the system's deviation of 5-8%, the proposed methodology would allow an increase in profit of 1-2.5%.

It is also very interesting to note that the proposed approach shows that under the current price structure of the Iberian market, the optimal bid only depends on the direction of the deviation of the electricity system, which implies that when implementing the approach proposed in this paper, operators can establish their bid on only one variable subject to uncertainty (the system deviation), which greatly simplifies the optimal bidding strategy.

Likewise, an alternative price scenario has been proposed in the second case study, increasing the responsibility from an economic point of view of the deviations produced by the generation units with the objective of emulating a possible price structure in a scenario of high penetration of variable energy sources. This second case study shows even greater potential for improving the proposed methodology over the classic approach that would achieve 19.6% under the assumption that prices and system deviation are previously known. However, the sensitivity analysis carried out on this second case including price uncertainty and system deviation shows that a range of improvement through the proposed methodology between 5-10% for errors within the range of 5-8% in the previously mentioned variables.

The potential for improvement achieved through the proposed methodology is in line with those documented in other previous works. However, it should be noted that the results are not directly comparable, since our work is the first to formulate the problem analytically through the price of the DAM plus the four existing prices in the BSs which in turn depend on the direction of the system deviation, as is currently the case in the Spanish system.

5. Conclusions

The growth in the participation of WFs in the liberalized electricity markets has brought an important challenge due to the variability of the wind energy production and forecasts uncertainty. This work has proposed a novel method to calculate the optimal bidding strategy for a WF by an analytical maximization of the expected income function, depending on the energy bidding. The proposed method is easy to implement in both already operational or planned WFs, since it is based on data that every WFO has available from its SCADA system and from the energy production forecasts needed to participate in the market. Therefore, the implementation of the methodology does not require any additional investment and only consists of modifying the bidding strategy. Likewise, the proposed method is also easily adaptable to different organized markets other than the Spanish system, and its implementation can be extended to other variable renewable technologies, such as solar photovoltaic.

The potential of the proposed approach has been validated by using actual forecast and production data from a real 28 MW WF located in Spain. The proposed methodology is based on the initial validation of a novel approach by the analytical optimization of the problem. To this end, all the variables involved in calculating the actual income of a WF have been considered in the formulation, such as DAM prices, as well as the four prices of BS depending on overall deviation of the electricity system. The initial validation of the proposed methodology shows a great potential for improvement in revenues with respect to the conventional bidding strategy based on bidding the forecasted energy.

Two test cases have been analysed, the first test case considers actual data for both the plant generation and forecasts, as well as realistic hourly DAM and BS price data of the Spanish system. However, in the case of Spanish BS, the price formation structure leads to the fact that the WF can establish an optimal supply strategy based solely on the deviation of the electricity system, which could lead to an increase in the system's balancing needs, affecting to the operation of the whole system. Therefore, the analysis of a second case is proposed, by considering modified prices of the BS so that in all cases WFs are responsible for their deviations, which could be more appropriate in a future scenario of greater renewable penetration in the electricity system. The methodology proposed in the present work has demonstrated to be satisfactory with a noticeable range of improvement in the income for all the cases analysed.

Additionally, the analysis carried out on a real case in the Iberian market provides important conclusions from the point of view of energy policies, since the current design of BS in Spain does not penalize all deviations produced by generators, which in future can lead to inefficient management of the whole electricity system. This is especially important in a scenario of high penetration of renewables, such as that foreseen in the Spanish National Energy and Climate Plan , which foresees by 2030 a 74% share of renewables in the electricity system doubling variable renewable energy sources' current installed capacity from approximately 30 GW at present to a total of 90 GW by 2030.

Acknowledgments

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References

[1] OMIE, Daily and Intraday Electricity Market Operating Rules, 2014.

[2] A. Ahmed, M. Khalid, A review on the selected applications of forecasting models in renewable power systems, Renewable and Sustainable Energy Reviews. 100 (2019) 9–21. https://doi.org/10.1016/j.rser.2018.09.046.

[3] T. Jónsson, P. Pinson, H. Madsen, On the market impact of wind energy forecasts, Energy Economics. 32 (2010) 313–320. https://doi.org/10.1016/j.eneco.2009.10.018.

[4] Y. Zhang, J. Wang, X. Wang, Review on probabilistic forecasting of wind power generation, Renewable and Sustainable Energy Reviews. 32 (2014) 255–270. https://doi.org/10.1016/j.rser.2014.01.033.

[5] M. Lv, S. Lou, B. Liu, Z. Fan, Z. Wu, Review on power generation and bidding optimization of virtual power plant, in: Proceedings - 2017 International Conference on Electrical Engineering and Informatics: Advancing Knowledge, Research, and Technology for Humanity, ICELTICs 2017, Institute of Electrical and Electronics Engineers Inc., 2018: pp. 66–71. https://doi.org/10.1109/ICELTICS.2017.8253242.

[6] J. Dhillon, A. Kumar, S.K. Singal, Optimization methods applied for Wind-PSP operation and scheduling under deregulated market: A review, Elsevier Ltd, 2014. https://doi.org/10.1016/j.rser.2013.11.009.

[7] I.G. Moghaddam, M. Nick, F. Fallahi, M. Sanei, S. Mortazavi, Risk-averse profit-based optimal operation strategy of a combined wind farm-cascade hydro system in an electricity market, Renewable Energy. 55 (2013) 252–259. https://doi.org/10.1016/j.renene.2012.12.023.

[8] R. Laia, H.M.I. Pousinho, R. Melíco, V.M.F. Mendes, Bidding strategy of wind-thermal energy producers, Renewable Energy. 99 (2016) 673–681. https://doi.org/10.1016/j.renene.2016.07.049.

[9] E. Baeyens, E.Y. Bitar, P.P. Khargonekar, K. Poolla, Coalitional Aggregation of Wind Power, IEEE Transactions on Power Systems. 28 (2013) 3774–3784. https://doi.org/10.1109/TPWRS.2013.2262502.

[10] V. Guerrero-Mestre, A.A.S. de la Nieta, J. Contreras, J.P. Catalao, Optimal bidding of a group of wind farms in day-ahead markets through an external agent, IEEE Transactions on Power Systems. 31 (2015) 2688–2700.

[11] J. Usaola, M.Á. Moreno, Optimal bidding of wind energy in intraday markets, in: 2009 6th International Conference on the European Energy Market, EEM 2009, 2009. https://doi.org/10.1109/EEM.2009.5207179.

[12] J. Usaola, J. Angarita, Bidding wind energy under uncertainty, in: 2007 International Conference on Clean Electrical Power, ICCEP ’07, 2007: pp. 754–759. https://doi.org/10.1109/ICCEP.2007.384298.

[13] M. Bueno, M.Á. Moreno, J. Usaola, F.J. Nogales, Strategic wind energy bidding in adjustment markets, in: 45th International Universities Power Engineering Conference UPEC2010, IEEE, 2010: pp. 1–6.

[14] H. Holttinen, Optimal electricity market for wind power, Energy Policy. 33 (2005) 2052–2063. https://doi.org/10.1016/j.enpol.2004.04.001.

[15] P. Pinson, C. Chevallier, G.N. Kariniotakis, Trading wind generation from short-term probabilistic forecasts of wind power, IEEE Transactions on Power Systems. 22 (2007) 1148–1156. https://doi.org/10.1109/TPWRS.2007.901117.

[16] G.N. Bathurst, J. Weatherill, G. Strbac, Trading wind generation in short term energy markets, IEEE Transactions on Power Systems. 17 (2002) 782–789. https://doi.org/10.1109/TPWRS.2002.800950.

[17] J. Matevosyan, L. Söder, Minimization of imbalance cost trading wind power on the short-term power market, IEEE Transactions on Power Systems. 21 (2006) 1396–1404. https://doi.org/10.1109/TPWRS.2006.879276.

[18] K. Afshar, F.S. Ghiasvand, N. Bigdeli, Optimal bidding strategy of wind power producers in pay-as-bid power markets, Renewable Energy. 127 (2018) 575–586. https://doi.org/10.1016/j.renene.2018.05.015.

[19] J.M. Morales, A.J. Conejo, H. Madsen, P. Pinson, M. Zugno, Trading stochastic production in electricity pools, in: International Series in Operations Research and Management Science, Springer New York LLC, 2014: pp. 205–242. https://doi.org/10.1007/978-1-4614-9411-9_7.

[20] C.J. Dent, J.W. Bialek, B.F. Hobbs, Opportunity cost bidding by wind generators in forward markets: Analytical results, IEEE Transactions on Power Systems. 26 (2011) 1600–1608.

[21] E.Y. Bitar, R. Rajagopal, P.P. Khargonekar, K. Poolla, P. Varaiya, Bringing Wind Energy to Market, IEEE Transactions on Power Systems. 27 (2012) 1225–1235. https://doi.org/10.1109/TPWRS.2012.2183395.

[22] S. Li, C.S. Park, Wind power bidding strategy in the short-term electricity market, Energy Economics. 75 (2018) 336–344. https://doi.org/10.1016/j.eneco.2018.08.029.

[23] B. Douglas, G. Brindley, M. Labordena, S. Dunlop, Introduction to Corporate Sourcing of Renewable Electricity in Europe, 2020.

[24] IBERDROLA, Do you know what an energy PPA is? - Iberdrola, (2020). https://www.iberdrola.com/press-room/top-stories/contracts-ppa-energy (accessed April 3, 2020).

[25] BOE Royal Decree which stablishes the rules to participate in the system adjustment services, 2015.

[26] Markets and prices | ESIOS electricity · data · transparency. https://www.esios.ree.es/en/market-and-prices (accessed April 3, 2020).

Annex

Table A1 shows the histogram that approximates the PDF for a 24h lag time obtained according to the data analysed in the WF under study during the first half of 2016. Each row refers to an energy forecast interval, while each column refers to the energy finally generated. Thus, the *ij*-th element of the table represents the probability in percentage that the energy forecast corresponding to the *i*-th interval has an actual energy production corresponding to the *j*-th interval.

Table A1. Probability histogram for a 24h lag time

		Actual energy produced																											
		[0,1)	[1,2)	[2,3)	[3,4)	[4,5)	[5,6)	[6,7)	[7,8)	[0,1)	[8,9)	[9,10)	[10,11)	[11,12)	[12,13)	[13,14)	[14,15)	[15,16)	[16,17)	[17,18)	[18,19)	[19,20)	[20,21)	[21,22)	[22,23)	[23,24)	[24,25)	[25,26)	[27,28]
Forecsted energy (MWh)	[0,1)	43.9	17.8	13.4	6.8	4.4	2.7	2.7	1.7	0.7	0.7	0.5	0.5	0.5	0.5	0.7	0.2	0.2	0.2	0.2	0.5	0.0	0.2	0.2	0.2	0.0	0.0	0.0	0.2
	[1,2)	23.2	17.9	12.3	10.2	8.7	5.7	4.7	3.4	3.2	1.9	1.5	1.9	0.9	0.4	0.9	0.6	0.2	0.6	0.4	0.0	0.2	0.0	0.2	0.0	0.2	0.0	0.4	0.2
	[2,3)	19.5	14.0	10.6	12.0	9.2	7.4	6.0	4.6	4.3	3.2	3.2	1.4	1.1	0.9	1.1	0.9	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3
	[3,4)	6.1	9.2	8.0	9.2	10.8	8.0	7.6	6.7	4.1	5.7	4.5	4.8	4.1	3.5	1.3	2.2	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.3	0.6	1.0
	[4,5)	5.8	4.1	6.5	10.9	6.5	5.8	11.2	8.8	7.8	10.5	4.4	4.1	3.1	2.0	0.7	1.7	1.0	0.7	0.7	0.3	1.0	0.7	0.7	0.0	0.3	0.0	0.3	0.3
	[5,6)	2.4	2.8	5.2	5.6	7.6	8.4	6.4	11.6	9.6	6.8	6.0	3.2	4.4	3.6	2.4	2.8	2.8	1.6	1.2	0.8	2.8	0.4	0.4	1.2	0.0	0.0	0.0	0.4
	[6,7)	2.6	3.5	4.4	2.6	4.0	5.3	5.7	5.3	12.8	7.9	4.0	5.3	5.7	6.6	3.1	4.0	2.6	3.5	1.8	2.6	0.9	1.3	0.9	1.3	0.4	0.9	0.0	0.9
	[7,8)	2.1	1.1	1.6	2.1	3.2	5.9	3.2	8.0	9.0	6.4	8.0	6.9	6.4	4.3	3.7	2.1	5.9	2.1	3.7	2.1	4.8	1.6	1.1	1.6	1.1	0.5	1.1	0.5
	[0,1)	1.7	0.6	3.9	1.7	2.8	6.1	6.1	6.1	9.4	9.9	6.6	7.2	8.3	4.4	2.2	3.3	3.9	1.1	2.2	3.3	0.6	2.2	1.1	0.6	2.2	0.6	0.6	1.7
	[8,9)	2.0	1.4	4.1	1.4	2.0	7.4	10.1	7.4	6.1	6.1	6.1	4.7	3.4	7.4	7.4	2.7	2.0	3.4	3.4	2.7	2.7	1.4	0.7	0.7	1.4	0.7	0.7	0.7
	[9,10)	2.7	0.9	0.9	4.4	4.4	0.9	2.7	8.0	8.8	8.8	6.2	9.7	5.3	6.2	2.7	3.5	5.3	5.3	0.0	2.7	3.5	0.9	0.9	1.8	0.0	0.0	1.8	1.8
	[10,11)	1.8	0.0	1.8	5.3	1.8	4.4	6.1	1.8	9.6	6.1	7.0	4.4	8.8	3.5	4.4	4.4	3.5	6.1	4.4	6.1	1.8	1.8	0.9	0.9	0.0	0.9	1.8	0.9
	[11,12)	2.2	2.2	2.2	4.3	3.3	2.2	2.2	3.3	8.7	7.6	2.2	5.4	5.4	4.3	8.7	7.6	5.4	4.3	2.2	3.3	2.2	3.3	4.3	0.0	2.2	0.0	0.0	1.1
	[12,13)	1.4	0.0	1.4	0.0	0.0	5.6	1.4	4.2	5.6	5.6	5.6	5.6	5.6	2.8	14.1	4.2	7.0	7.0	1.4	4.2	4.2	4.2	2.8	0.0	1.4	1.4	0.0	2.8
	[13,14)	1.2	0.0	1.2	1.2	2.3	4.7	2.3	3.5	9.3	9.3	3.5	5.8	2.3	11.6	7.0	4.7	1.2	2.3	5.8	5.8	3.5	1.2	2.3	1.2	1.2	1.2	3.5	1.2
	[14,15)	2.3	0.0	0.0	0.0	4.5	0.0	2.3	0.0	3.4	3.4	3.4	6.8	11.4	10.2	4.5	8.0	5.7	5.7	9.1	5.7	1.1	3.4	2.3	3.4	1.1	1.1	0.0	1.1
	[15,16)	2.2	0.0	2.2	3.3	2.2	0.0	0.0	2.2	2.2	2.2	7.7	4.4	4.4	3.3	9.9	2.2	8.8	8.8	6.6	6.6	5.5	4.4	3.3	2.2	4.4	0.0	0.0	1.1
	[16,17)	3.6	0.0	0.0	0.0	1.2	1.2	1.2	3.6	0.0	2.4	6.0	4.8	6.0	4.8	0.0	8.4	6.0	6.0	7.2	6.0	9.6	6.0	8.4	0.0	2.4	1.2	2.4	1.2
	[17,18)	1.1	0.0	0.0	0.0	2.2	0.0	0.0	0.0	3.3	1.1	1.1	3.3	5.6	5.6	5.6	4.4	10.0	7.8	8.9	5.6	6.7	3.3	5.6	5.6	6.7	2.2	2.2	2.2
	[18,19)	1.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.3	3.8	1.3	0.0	3.8	3.8	5.1	3.8	9.0	5.1	6.4	3.8	10.3	5.1	15.4	7.7	2.6	2.6	6.4	1.3
	[19,20)	1.6	1.6	1.6	1.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.7	1.6	0.0	4.7	17.2	10.9	6.3	12.5	7.8	3.1	6.3	1.6	6.3	10.9
	[20,21)	1.4	0.0	0.0	1.4	1.4	0.0	1.4	1.4	0.0	1.4	1.4	0.0	1.4	2.8	1.4	1.4	5.6	1.4	5.6	5.6	9.7	11.1	5.6	6.9	9.7	6.9	6.9	8.3
	[21,22)	1.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.9	0.0	1.9	0.0	0.0	0.0	0.0	0.0	3.8	1.9	3.8	7.7	7.7	5.8	7.7	19.2	11.5	25.0
	[22,23)	2.4	0.0	0.0	4.8	2.4	0.0	4.8	2.4	2.4	0.0	0.0	4.8	2.4	7.1	7.1	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	7.1	4.8	7.1	19.0
	[23,24)	2.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.6	0.0	0.0	0.0	0.0	2.6	0.0	5.3	0.0	2.6	2.6	0.0	7.9	15.8	10.5	15.8	13.2	18.4
	[24,25)	3.3	0.0	0.0	0.0	3.3	0.0	0.0	3.3	3.3	3.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.0	0.0	3.3	0.0	3.3	10.0	10.0	3.3	10.0	3.3	30.0
	[25,26)	7.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.7	0.0	15.4	23.1	0.0	7.7	7.7	7.7	7.7	15.4
	[27,28]	8.3	0.0	0.0	0.0	0.0	4.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.2	0.0	0.0	0.0	33.3	20.8	29.2