Optimal bidding of wind farms in electricity markets considering the influence of system deviation

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***Abstract*— This work presents a methodology for optimal energy bidding of renewable energy plants based on an analytical framework combined with artificial neural networks to predict the main variables involved in the proposed problem. The optimal bid made by a renewable generator relies on the most accurate forecast available at the time the energy bid is submitted to the spot market, typically between 12 to 36 hours before the delivery time. Given these lead times, renewable generators face a considerable volume risk due to potential discrepancies between the energy actually delivered and the energy initially committed to in the market. Any deviations from the committed energy are settled at the deviation price. This study highlights that deviation prices are heavily influenced by the system's need to increase or decrease energy at the time of delivery. In other words, if the generator's deviation is detrimental to the system's balance, the generator will typically face a higher penalty, paying a deviation cost above the spot market price. Conversely, if the deviation benefits the system, the penalty will be significantly lower, potentially even zero.**

***Index Terms*-- electricity balancing markets, electricity day-ahead market, wind power bidding, wind energy.**

I. INTRODUCTION

A key challenge for wind energy participation in liberalized electricity markets lies in the variability of wind speed. In Europe, recent legislative efforts by the European Commission aim to redesign the electricity market to better accommodate renewable energy sources, particularly variable generation. However, most European markets, including the Iberian market (shared by Spain and Portugal as part of the internal European market), require generators to submit bids in the day-ahead market (DAM) 12-36 hours before dispatch. This timeframe presents significant forecasting uncertainty for wind energy, which often leads to penalties for deviations. Although intraday markets (IM) allow for bid adjustments, the required lead time of 3-14 hours still leaves wind generators exposed to considerable risk due to the inherent unpredictability of wind.

Research on how forecasting impacts renewable participation in DAMs is extensive. Ahmed et al. [1] provided a comprehensive analysis of forecasting in renewable dispatch, energy storage, and market impacts, among other topics. Jónsson et al. [2] explored how wind power forecasts influence market prices, particularly in regions with high wind penetration, such as Denmark's DK-1 zone in the Nord Pool market. They found a strong correlation between forecasted wind generation relative to demand and spot prices. Similarly, Zhang et al. [3] reviewed probabilistic methods for wind forecasting, highlighting wind speed variability and wind-to-power conversion as major sources of uncertainty.

To address these forecasting challenges, hybridization has been proposed as a potential solution. For instance, hybrid wind-storage systems could enhance market participation by mitigating variability. Dhillon et al. [4] analyzed the role of wind-pumped storage plants in balancing markets, emphasizing their ability to increase wind energy penetration. Other studies, such as Moghaddam et al. [5], developed models to optimize the market participation of combined wind-hydro systems, demonstrating how penalty mechanisms influence bidding strategies. Similarly, Laia et al. [6] proposed a joint bidding approach for wind farms and thermal units, showing that coordinated strategies can improve market revenue.

Several analytical approaches have explored the use of probability density functions (PDFs) for optimizing renewable energy bidding strategies. Morales et al. [7] proposed a conceptual framework to determine optimal trading strategies for renewable plants in the day-ahead market (DAM) and balancing markets (BMs). They analyzed the interplay between these markets, emphasizing that bids in the BMs are often influenced by prior bids in the DAM. However, the study remained theoretical and did not include numerical validations.

Subsequent studies have delved deeper into this topic. Dent et al. [8] used data from the Great Britain market to assess optimal bidding under various scenarios, focusing on the correlation between wind farm production and real-time prices. They examined single and dual imbalance pricing mechanisms and considered the influence of conventional generation on wind farm bidding. Similarly, Bitar et al. [9] explored the

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impact of forecasting uncertainties on market strategies. Their work proposed integrating small thermal plants alongside wind farms to mitigate imbalances, analyzing the reserve margin's role in systems with high renewable penetration. Empirical results were derived using data from 14 U.S. wind farms.

Li and Park [10] presented one of the latest advancements in this area, focusing on optimal bidding in DAMs and real-time markets (RTMs) using data from the PJM market in the U.S. Their study incorporated various uncertainties, including locational marginal prices (LMPs) and wind power prediction errors. By modeling prediction errors with beta distribution functions, they demonstrated that bids based on these PDFs could increase revenue by up to 6.7% compared to using historical generation data.

This paper builds on these foundations by introducing a novel analytical framework tailored to the Iberian market (Spain and Portugal). This study contributes to the advancement of existing research by proposing a method that leverages real energy production forecasts. This approach allows for the characterization of uncertainty through probability density functions (PDFs) and facilitates an analytical strategy for optimizing the expected revenue of the wind farm. Unlike prior studies, this work incorporates daily market prices alongside four deviation prices, modeled using a system deviation variable. This formulation provides a realistic method to develop optimal bidding strategies under the current Iberian market structure.

It is also necessary to point out that this work is a continuation of our previous paper [11], in which the fundamentals of the proposed approach were introduced in a theoretical way (considering perfect information in the variables subject to uncertainty). In the present work, we move towards a realistic tool by introducing prediction algorithms for each of the variables subject to uncertainty present in the formulation of the problem. That is, prediction algorithms have been implemented for all the time series involved in the problem, including spot market prices, deviation prices, as well as system deviation prediction.

After this brief introduction, the rest of the paper is organized as follows: Section 2 introduces the problem formulation, Section 3 provides an overview of the implemented methodology, Section 4 presents the results obtained in the test cases, and finally, the conclusions are provided in Section 5.

II. PROBLEM FORMULATION

At a given time, the wind farm operator (WFO) must submit a bid for the day-ahead market (DAM) corresponding to hour *t*. This bid is based on a production forecast $Ef(t)$ provided with a lead time k. For simplicity, the lead time is omitted from the equations in the subsequent formulation. During hour, t, the wind farm will produce an actual energy output $Ep(t)$, which may differ from the bidding amount $Eb(t)$. Depending on this discrepancy, the WFO will incur either penalties or additional incomes.

The objective of the methodology presented in this paper is to maximize the total income from participation in both the DAM and balancing services (BSs). To achieve this, the method evaluates the probability of the actual energy output Ep being greater than or equal to the bid Eb, as described in Equation (1), or alternatively, in Equation (2).

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

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

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

The anticipated revenue, B, for a given scheduling interval, t, can be represented by (3).

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

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:

where λ is the marginal price of the day-ahead market, C_p^+ is the cost of a positive deviation of the wind farm output (in case there is a generation surplus with respect to the energy bidden in the day-ahead market) when the system's deviation is positive (i.e., the overall energy generation in the system is actually higher than scheduled), C_p^- is the cost of a negative deviation when the system's deviation is positive, C_n^+ is is the cost of a positive deviation when the system's deviation is negative, and C_n^- is the cost of a negative deviation when the system's deviation is negative. Additionally, β represents the probability of the system's deviation being positive, while $(1-\beta)$ is the probability of the system's deviation being negative.

This formulation models the expected income by considering the four existing prices in the balancing services and the probability of system deviations. It effectively captures the challenge of optimal energy supply for wind farms in the Spanish electricity market, aligning with the operation scheme of the day-ahead market and the balancing services in the Iberian electricity market.

It should be noted that all formulations in this paper refer to costs to the system/market, which are equivalent to the selling price for the energy produced by the plant. To determine the maximum expected income, equation (3) is derived as a function of the energy bidden.

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

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

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

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

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

where E_b^* represents the optimal energy bid. Once the optimal value of $F(E_b)$ is determined using equation (6), the corresponding value of E_b^* can be obtained by considering the probability density function (PDF) of the actual energy production for a given energy forecast. The value $F(E_b^*)$, derived from equation (6), corresponds to the cumulative distribution function (CDF) associated with E_b^*. The costs of the diversions have been collected from the information system of the Spanish System operator [12].

III. METHODOLOGY DESCRIPTION

WFOs must consider various factors when determining their energy bids for the DAM. Typically, operators rely on energy forecasts, often submitting bids equal to the forecasted value. However, this approach involves the risk of incurring penalties due to inaccuracies in the forecasts. To mitigate this, the methodology presented in this paper provides a more reliable solution by accounting for forecast uncertainty through the use of probability density functions (PDFs) that characterize the actual production of the wind farm. These PDFs are derived from historical forecast data over a training period and are based on hourly wind production forecasts provided by a specialized wind energy forecasting company for a real Spanish wind farm. As illustrated in Fig. 1, the PDFs, along with additional inputs such as the forecasted energy for the hour, DAM prices, system deviations (generation surplus or deficit), and deviation costs (calculated according to Spanish regulations), feed into a module designed to calculate the expected income function. This function allows the analytical determination of the optimal energy bid for each delivery period, typically one hour in the Iberian market. The methodology assumes that wind farms act as price-takers, submitting bids at zero price.

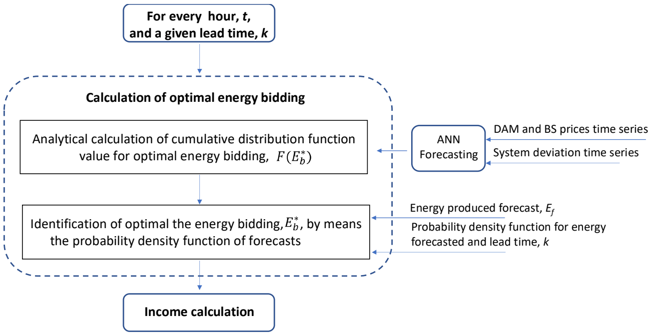

Figure 1. Overview of the proposed methodology

The process involves two main steps. First, the cumulative probability function is analyzed to identify the value that maximizes the expected income, considering DAM and BS prices as well as system deviations. Second, this value is used to determine the corresponding optimal energy bid numerically through the PDF. The proposed method is flexible and can be applied to different lead times, market sessions (e.g., DAM or intraday markets), and timeframes depending on the availability of forecast data.

A. System deviation and prices prediction method

As shown in Fig. 1, the proposed methodology requires forecasting algorithms to predict time series subject to uncertainty. That is, the spot market prices, imbalance costs, and system imbalance (note that it is also necessary to consider wind power production forecasts, but these are provided by a specialized meteorological forecasting company, so for the purposes of this work, they are considered an input).

To forecast imbalances and prices, an artificial neural network (ANN) has been implemented, for which different configurations with one and two hidden layers have been tested. The network with two hidden layers and seven neurons in each of them provided the best results. As shown in Fig. 2, this ANN takes as inputs the wind and photovoltaic generation forecasts, as well as the next day's demand forecast, data provided by the Transmission System Operator (REE) to market participants. Additionally, the ANN receives as input the system imbalances that occurred during the previous 24 hours, as well as information on the day of the week and the hour to be predicted. As a result, it provides a prediction of the system imbalance volume, which can be either negative or positive depending on whether the system has a generation deficit or surplus.

Similarly, to forecast spot market prices and imbalance costs, a neural network with two hidden layers and seven neurons in each of them has also been used. In this case, the ANN inputs are the wind, photovoltaic, and demand forecasts provided by REE, as well as information on the day of the week and the hour to be predicted, along with the imbalance prices/costs from the previous day and the same day of the previous week.

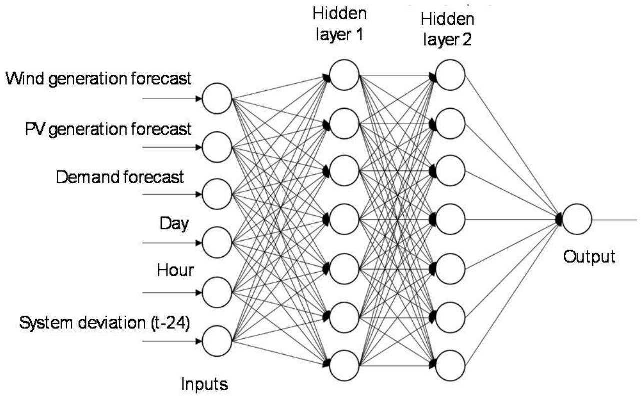

Figure 2. Implemented neural network for system deviation and prices predictions.

As can be seen in Equation (6), the problem can be formulated so that the system imbalance, β, is either a binary variable or can be approximated by the probability that the system imbalance takes a certain direction, depending on whether there was a generation surplus or deficit during the hour under study. However, the output of the implemented neural network is a prediction of the imbalance volume. Therefore, if the predicted system imbalance volume is positive, the variable β will take a unitary value, whereas if the predicted volume is negative, the variable β will be assigned a value of zero.

On the other hand, using the approach in which the variable β is approximated by the probability that the system imbalance is positive (therefore, 1 - β represents the probability that the system imbalance is negative), the imbalance volume prediction provided by the neural network will be used as described below.

Given a prediction of the system imbalance value, the probability that the prediction algorithm correctly determines the direction of the imbalance (or, in other words, correctly predicts whether it is positive or negative) will be determined based on the absolute value of the prediction. To achieve this, once the neural network has been trained with the data, a six-month prediction of imbalance values has been carried out to obtain the aforementioned probabilities.

This approach is based on the observation that the higher the absolute value of the imbalance prediction, the lower the probability that the neural network will fail in predicting the direction of the system imbalance. That is, when the predicted values are large and positive, the probability that the system imbalance will ultimately be positive is significantly higher than when the predicted values are close to zero (the same reasoning applies when the imbalance values are negative).

Fig. 3 illustrates this behavior for system imbalance predictions made 24 hours in advance over a two-year period. As can be seen, for absolute values of the system imbalance prediction close to zero (below 10 MW), the failure probability in predicting the imbalance direction is around 28%. However, as the absolute value of the prediction increases, this failure probability gradually decreases until, for absolute values of the prediction above 400 MW, the failure probability in determining the imbalance sign is practically zero.

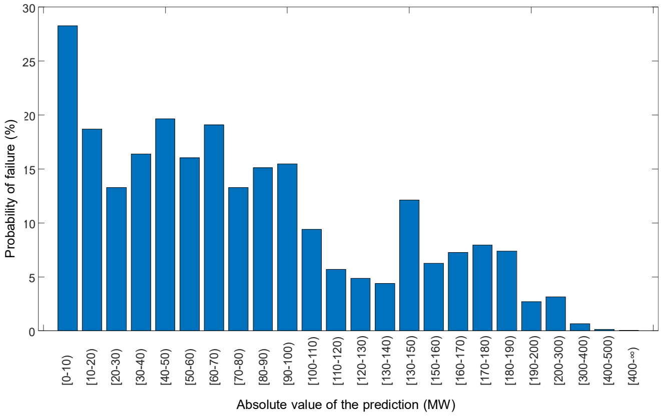

Figure 3. Failure probability of the system imbalance direction as a function of the absolute value of the prediction

Based on the results shown in Fig. 3, the direction of the system imbalance has been determined according to the predicted values obtained for the period under study in this work. To achieve this, when the prediction value is positive for a given hour (note that the system imbalance variable refers to the generation required to balance the system and, therefore, implies a negative deviation in the generation-consumption balance), the probability that the system imbalance is positive will be equal to the failure probability as a function of the absolute value of the imbalance prediction, according to the intervals used in the analysis shown in Fig. 3.

Similarly, when the prediction value is negative, the probability that the system imbalance is positive will be equal to one minus the failure probability, based on the absolute value of the given prediction.

IV. TEST CASES

In this study, a real 28 MW wind farm has been used as the basis for the analysis. The wind farm consists of 14 wind turbines of the Vestas V80-2.0 model. For this wind farm, real production data is available in hourly intervals, along with 24-hour-ahead forecasts for the time of delivery.

This data has allowed the approximation of the PDF by constructing a histogram that represents the probability that, given a forecasted energy generation value, the actual production will take any value within the wind farm's production range. The process of obtaining the PDFs begins by discretizing the potential generation values of the wind farm into a set of predefined intervals. Then, for each forecasted energy interval, the occurrences of the corresponding actual energy values are recorded using the same discretization scheme. Subsequently, the PDF for each forecasted interval is estimated by constructing a histogram, which is obtained by dividing the occurrences in each generated energy interval by the total number of samples for that forecasted interval. This method facilitates the systematic derivation of the PDF using historical data, which is readily accessible to wind farm operators. In this study, a discretization interval of 1 MWh is applied to both generated and forecasted energy values, resulting in a PDF represented as a 28 × 28 matrix for the selected lead time of 24 hours.

This matrix, along with the time series (day-ahead market price, imbalances, and actual wind farm production) considered for the execution of the case study, is provided as supplementary material in [13]. Note that the study focuses on a full year, with the first six months used for training the prediction models and characterizing the PDF, while the second six months of the analyzed year were used for executing the case studies.

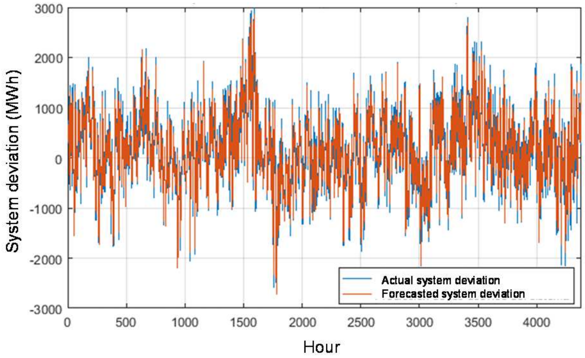

Figure 4. Actual and forecasted system deviation volume.

Figure 4 shows the comparison between the direction of the actual system imbalances for the second half of the analyzed year and the direction of the predicted values calculated using the neural network. Despite the fact that the MDAPE is relatively high (18.69%) when comparing both directions (actual and predicted), the predicted variable is incorrect in only 278 out of the 4,380 analyzed hours, representing 6.35% of the total hours in the period.

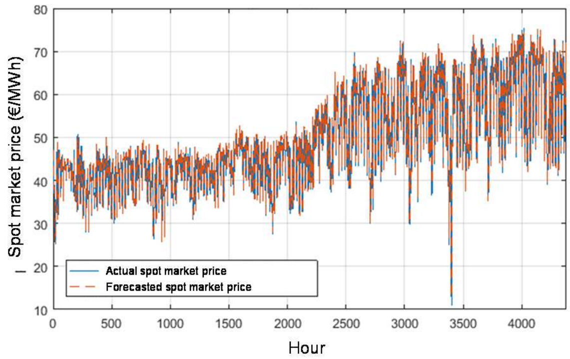

Figure 5. Actual and forecasted spot market price.

The results of the day-ahead market price prediction are presented in Figure 5. Over the entire period analyzed, the MAPE error was 1.27%, demonstrating a high level of accuracy in the estimation.

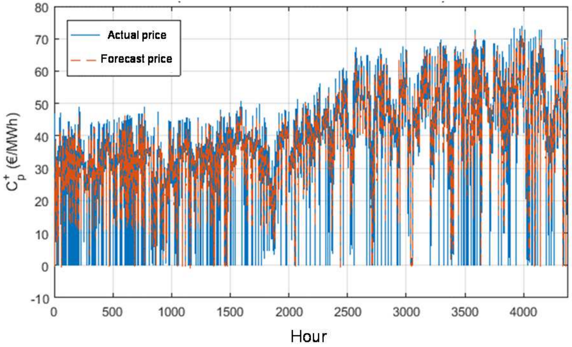

Figure 6. Actual and forecasted deviation cost for the case where the plant imbalance is positive, given that the system imbalance is also positive.

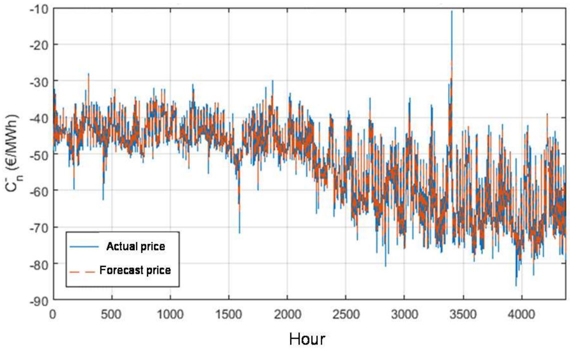

Figure 7. Actual and forecasted deviation cost for the case where the plant imbalance is positive, given that the system imbalance is also positive.

Figure 5 shows the prediction of the positive imbalance cost when the system imbalance is also positive, demonstrating a strong ability to capture the trend. In this case, the MDAPE error is 3.789. Additionally, as can be seen in Figure 6, the predicted variable corresponding to the imbalance cost for negative deviations when the system deviation is also negative (dashed red line) closely follows the actual series values (blue line). The MAPE associated with this prediction is 2.18%.

TABLE I. OBTAINED RESULTS FOR THE ANALYSED CASES

Analyzed Case	**Revenue (€)**	**Percentage Improvement**
Typical Offer	882,190	-
Case 1	909,480	3.09%
Case 2	914,100	3.62%
Theoretical Maximum	924,910	4.62%

Finally, Table I shows the results obtained after applying the proposed methodology to the wind farm under study, considering two cases: one where the system imbalance, β, is treated as a binary variable (Case 1) and another where it is formulated as the probability of the system imbalance being positive (Case 2), following the procedure introduced in Section III.

Both cases are compared with a typical offer approach, in which the plant bids the predicted energy, and with the theoretical maximum, where the plant bids the actual generated energy. As can be seen, the performance of the proposed methodology is satisfactory, improving revenues compared to the typical offer by 3.09% (Case 1) and 3.62% (Case 2), in both cases remaining relatively close to the theoretical maximum.

V. CONCLUSION

This study introduces a novel approach to determine the optimal bidding strategy for a wind farm by analytically maximizing the expected revenue function with respect to the energy bid. The proposed method is straightforward to apply in both operational and planned wind farms, as it utilizes data readily available from the SCADA system and the energy production forecasts required for market participation. Consequently, implementing this approach requires no additional investment, as it only involves adjusting the existing bidding strategy.

Additionally, the method is highly adaptable to other organized electricity markets outside of Spain and can be applied to other variable renewable energy sources, such as solar photovoltaic, or to any other generation or consumption source with forecast uncertainties.

The effectiveness of the proposed methodology has been validated using real forecast and production data from a 28 MW wind farm located in Spain. This approach relies on an analytical optimization of the problem, taking into account all relevant factors affecting the plant's actual revenues, including day-ahead market prices and the four types of imbalance costs related to the overall system imbalance. The initial validation results indicate a substantial potential for revenue enhancement compared to the conventional bidding strategy of offering the forecasted energy.

TABLE II. SENSITIVITY ANALYSIS TO THE ERROR IN PREDICTING THE DIRECTION OF SYSTEM IMBALANCE: PERCENTAGE OF IMPROVEMENT

$\boldsymbol{\beta}$ error prediction (%)	1	2	3	4	5	6	7	8	9	10
Improvement (%)	4.13	3.67	3.22	2.76	2.30	1.85	1.39	0.94	0.48	0.02

Table II shows the results of a sensitivity analysis carried out to evaluate the effectiveness of the proposed approach. Starting from a perfect information scenario and assuming a 5% error in the cost prediction algorithms, the error in forecasting the probability of a positive system imbalance was varied—also incorporating a random component—within a range from 1% to 10%. The results reveal a linear relationship between the accuracy of the imbalance prediction and the improvement percentage achieved by the proposed method.

ACKNOWLEDGMENT

This paper is part of the research project PID2021-127550OA-I00 funded by MICIU/AEI/ 10.13039/501100011033 and by the EU/ERDF.

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