Danmarks Tekniske Universitet

31761 Renewables in Electricity Markets

Assignment 2

Participation of a renewable energy producer in the electricity market

Authors

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April 14, 2019

Contents

1 Introduction

This report is a follow up of the work developed on the first assignment where an optimization problem was solved to replicate the real-world problem of a day-ahead market. This time, we investigate different strategies of placing bids on the day-ahead market in order to always have the highest revenue resulting of the day-ahead and balancing market outcomes combined.

This report will first introduce a detailed formulation of how the revenues are calculated in a real-world market, then we set the reference as being an ideal scenario of placing bids in the market. Next, we go in depth on the description of three different types of strategies that were approached in this work: a base strategy, a deterministic and a probabilistic strategy. Each one providing different revenues and performance factors. Lastly, all these strategies will be compared to the reference that was set and the results will be discussed.

2 Revenues Formulation

The yearly total revenue (R_T), used to evaluate the performance of each participation strategy, is based in the sum of revenues obtained in the day-ahead market (R_{DA}) and the results of the balancing market (R_B) over the year, and is mathematically described by Equation 1.

$$R_T = R_{DA} + R_B = \sum_{i=1}^{8760} \lambda_i^S \hat{E}_i + \sum_{j \in L_\downarrow} \lambda_j^\downarrow (E_j - \hat{E}_j) - \sum_{k \in L_\uparrow} \lambda_k^\uparrow (\hat{E}_k - E_k) \tag{1}$$

Where $L_\downarrow$ are all time units when the wind farm is producing more than what was promised in the day-ahead market (i.e, $E_k > \hat{E}_k$), $L_\uparrow$ are all time units when the wind farm is producing less than what was promised in the day-ahead market (i.e, $E_k < \hat{E}_k$), λ_i^S is the equilibrium price in the day-ahead market for time unit i, $\lambda_j^\downarrow$ is the down-regulation price for time unit j, and $\lambda_k^\uparrow$ is the up-regulation price for time unit k.

Depending on the different combination of values for λ_i^S, $\lambda_j^\downarrow$ and $\lambda_k^\uparrow$, one can define the system status of a specific time unit as follows:

- if $\lambda_j^\downarrow = \lambda_k^\uparrow$, the system is in balance.
- if $\lambda_j^\downarrow = \lambda_i^S$, the system is in up-regulation.
- if $\lambda_j^\uparrow = \lambda_i^S$, the system is in down-regulation.

When the system is in up-regulation, every producer that is generating more energy than expected is not going to be penalized, since the down-regulation price is equal to the day-ahead price. Power producers that are generating less energy than expected are penalized since they have to buy the energy difference with an up-regulation price that is higher than the day-ahead price. In this system scenario, the optimal strategy is to bid in the day-ahead market with the minimum allowed value.

On the other hand, when the system is in down-regulation, every producer that is generating less energy than expected is not going to be penalized, since the up-regulation price is equal to the day-ahead price. Power producers that are generating more energy than expected are penalized, since they are going to be paying for the extra energy at the down-regulating price, which is lower than the day-ahead market. In this system scenario, the optimal strategy is to bid in the day-ahead market with the maximum capacity of the power plant.

2.1 Ideal scenario

The revenues obtained using the strategies that are going to be described in Section 3 were compared to an ideal scenario, which reflects the maximum revenue that could be obtained with a perfect strategy. In this ideal situation, the predicted energy production would always be equal to the actual energy produced (i.e, $E_i = \hat{E}_i \ \forall \ i$), and all the energy would be sold in the day-ahead market. In order to compare the strategies, it is introduced a performance ratio γ, described by Equation 2

$$\gamma = \frac{R_T^{strategy}}{R_T^{ideal}} \tag{2}$$

3 Bidding Strategies Formulation

In this section we will discuss the implementation of three different strategies for bidding on the day-ahead market. The first one is a base strategy based on historical data, the second one is called a deterministic strategy where we simply used the forecast of wind power production available for any given time unit and, lastly, we implement a strategy based on probabilistic forecast data which will be divided into three different profiles based on different predicted "optimal" quantiles based on forecasts.

All of these strategies will be applied to the data available from the market of the year 2017.

3.1 Base Strategy

The so called base (*dummy*) strategy is formulated by analyzing the historical data available on Nordpool's website [1] of the prices for the day-ahead and balancing markets for each time unit from 2013 to 2016. From this data it was created a 24h profile plot, like the one in Figure 1, of how many times the system was in balance, up or down regulation for each hour of the day.

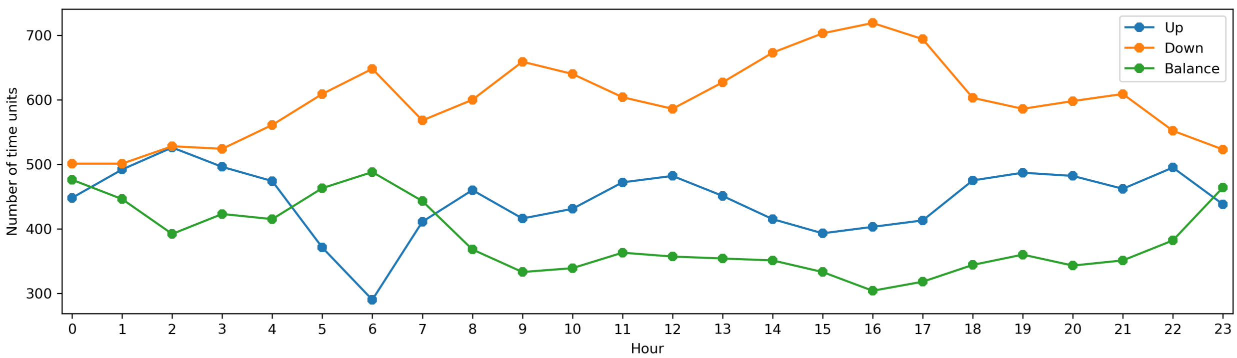

Figure 1: 24h profile of the number of occurrences of the balance of the system.

From Figure 1 it is easy to observe that the number of occurrences of down regulation in the system for every hour of the day is greater than up regulation of the system in balancing conditions. For this reason, it was chosen that the bid amount would be the full capacity of the analyzed wind farm, meaning that for every time unit, a bid of $160MW$ would be placed. This bidding strategy can be justified because the power plant can never produce more than $160MW$, in fact, in practice, even when working in great conditions, it will always produce less energy than its maximum capacity. Since, from the analysis above, the system will likely be in down regulation, delivering less power than what was initially offered on the day-ahead market would be helping the system to get back to the balancing condition. From a revenue point of view, the wind power operator will receive money based on its plant's capacity and the day-ahead market clearing price and will have to pay back a quantity concerning the difference in energy offered and what was actually produced and the price of either up or down regulation of the system.

Applying this strategy with the available data of the market prices of the year 2017 and the actual power produced by the wind farm yielded a total revenue of $R_T = 130,957,312.83$ for 2017. This strategy presented a performance ration $\gamma = 89.87599\%$

3.2 Deterministic Strategy

The next strategy to be evaluated in this section is a deterministic strategy. This option is formulated in a way that all the bidding quantities will rely simply on the deterministic forecast of wind power production provided, meaning that the wind farm operator trusts his forecast provider. It was always used the deterministic forecast issued at 12:00 of the day preceding the actual measurement, which reflects a real life situation without using information from the future. However, since the Day-ahead market closes at 12:00, it was assumed that the forecast is provided a couple of minutes before mid-day and we have time to process the data to place the bids.

This strategy is then applied to the 2017 day-ahead market and the revenue is again calculated according to Equation 1. This strategy provided the following revenue

$$R_T = 141,349,129.87 \tag{3}$$

With a performance ratio of $\gamma = 97.00789\%$.

In order to try to improve the results of this strategy, it is possible to play around with it by giving it an adjustment factor to the power production forecasts based on the potential balancing needs and costs given by

$$E_i = \tau \hat{y}_i, \quad i = 1, ..., 8760 \tag{4}$$

After a few attempts of selecting the best factor, we found the best τ to be approximately 2%, this adjustment factor yielded a new revenue of

$$R_T = 141,367,276.52 \tag{5}$$

which represents an increase in revenue of $R_T = 18,146.65$ with a new performance ratio of $\gamma = 97.02035\%$.

3.3 Probabilistic Strategy

This last set of strategies will be based on a probabilistic forecast of the wind power production at any given time unit i. The energy quantities to be offered in the market will be given by

$$E_i^* = \hat{F}_i^{-1}(\hat{\alpha}^*), \quad i = 1, ..., 8760 \tag{6}$$

Where $\hat{F}_i$ is the predicted cumulative distribution function for the wind power generation at a time unit i and $\hat{\alpha}^*$ represents the predicted optimal quantile based on forecasts and it is given by

$$\alpha_i^* = \frac{\pi^+}{\pi^+ + \pi^-} \tag{7}$$

where π^+ and π^- represent the marginal profit and loss, respectively, of the balancing markets and are given by

$$\pi^+ = \lambda_i^S - \lambda_i^{\downarrow} \tag{8}$$

$$\pi^- = \lambda_i^{\uparrow} - \lambda_i^S \tag{9}$$

This strategy will also be evaluated on the 2017 market with three different approaches for selecting a value for $\hat{\alpha}^*$, which indicates the optimal quantile that allows us to extract the bidding quantity from the wind power forecast data provided. This quantile forecast with a nominal level α tells that there is a probability of α that the actual measured energy produced on the given time unit will be less than the value given by this quantile. As for the deterministic strategy, it was always used the probabilistic forecast issued at 12:00 of the day preceding the actual measurement and it was assumed that the forecast is provided a couple of minutes before mid-day, so there is enough time to process the data to make the bids.

3.3.1 Historical Profile

The first attempt of the probabilistic strategy is based on a historical analysis of the market prices. This was implemented by first calculating all the π^+ and π^- for all the time units on the historical data available from 2013 to 2016. Next, we take the mean of both π^+ and π^- and lastly, we calculate one single α^* as in Equation 7, resulting in $\alpha_i^* = 0.50$, therefore, from our wind power forecast data, we will be selecting the energy quantities represented by the quantile $q(50)$. This strategy yielded a final revenue of $R_T = 141,403,854.44$ with a performance ratio $\gamma = 97.05\%$.

3.3.2 24-hour Profile

The second attempt of the probabilistic strategy uses the same historical market prices available from 2013 to 2016 used in the previous section. However, this time instead of averaging out π_i^+ and π_i^- for the entire data, we use them to calculate α_i^* as in Equation 7 for every time unit of the available data. Next, we create a 24h profile of the data similarly to what was done in Section 3.1, where we group all the α_i^* of the same hour of the day and then we compute the respective mean, resulting in 24 different values of α_i^*. This distribution of values over the 24h is displayed in Figure 2.

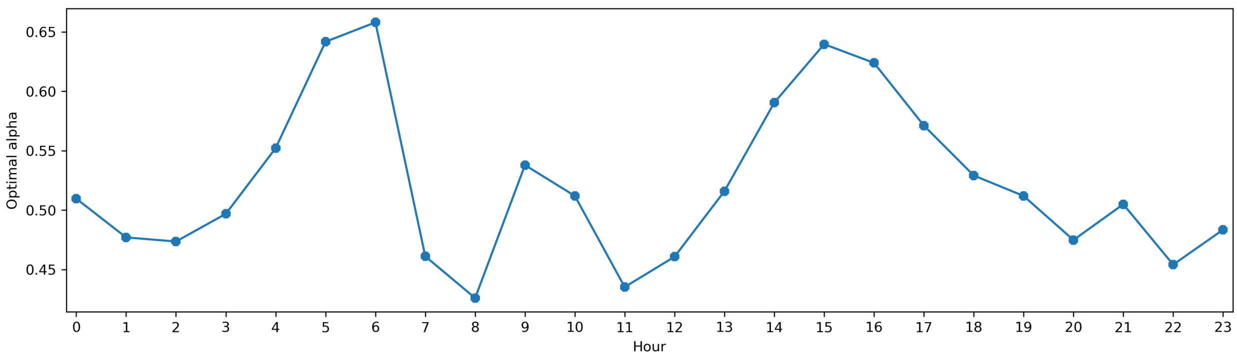

Figure 2: Optimal alpha using hourly mean.

Next, for each time unit of the 2017 market data, a value of α_i^* is assigned corresponding to the respective hour of the day. This value of α_i^* is used to get the energy quantity from its respective quantile in the wind power forecast data. This corresponds to the bid that will be placed in the day-ahead market.

Lastly, the final revenue for 2017 is calculated again using Equation 2 which resulted in a revenue of $R_T = 141,459,860.24$ with a performance ratio $\gamma = 97.08\%$

3.3.3 Monthly Profile

The last strategy to be investigated based on probabilistic forecast uses the same approach as the one described in Subsection 3.3.2. The difference is that instead of grouping the values of marginal cost and loss (π_i^+ and π_i^-) by the hour of the day, we chose to group them by the month of the year, trying to look for any seasonality influence and then averaging them so that we can calculate α_i^* for each month. The resulting profile of α_i^* is displayed in Figure 3. Similarly to what was done with the 24h profile, we replicate the corresponding values of α_i^* for every time unit of the 2017 market data. This will give us the quantile to be selected from the wind power forecast data that provides us with the energy quantity to be used to place the bid on the market. As in previous cases, we computed the revenue for this strategy which resulted in a total revenue of $R_T = 141,374,801.96$ with a performance ratio $\gamma = 97.03\%$.

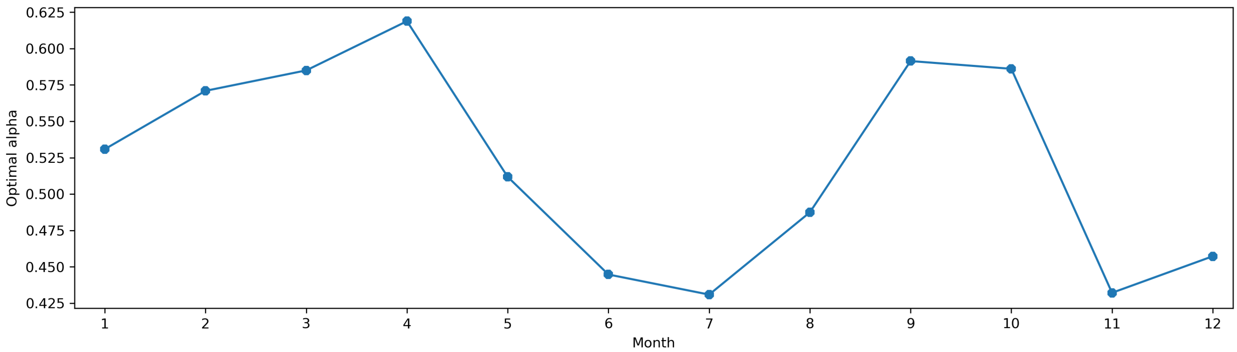

Figure 3: Optimal alpha using monthly mean.

3.4 Results

In this section, the results of the strategies are compared to each other, including an analysis of the revenues obtained in each scenario. Table 1 summarizes the results obtained in each strategy, which includes respective R_T and γ for the year of 2017. The revenues are also presented in the form of a plot, which can be seen in Figure 4.

Table 1: Revenue and performance ratio results.

Strategy	**Revenue [€]**	**Performance Ratio [%]**
Ideal	145,708,889.59	100
Base strategy	130,957,312.83	89.88
Deterministic forecast	141,367,276.52	97.02
Probabilistic forecast A	141,403,854.44	97.05
Probabilistic forecast B	141,459,860.24	97.08
Probabilistic forecast C	141,374,801.96	97.03

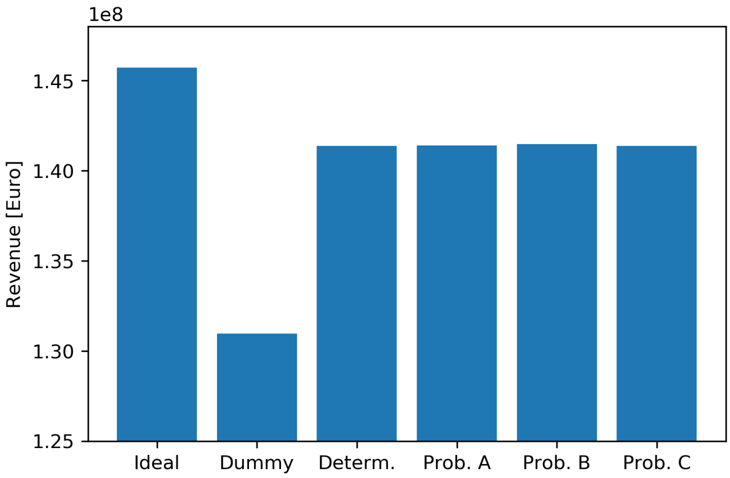

Figure 4: Comparison of participation strtegies' revenues.

From Figure 4, it is clear that the Deterministic strategy and the three Probabilistic strategies have a significant improvement when compared to the Base strategy. In fact, the improvements in relation to the Base strategy were:

- Deterministic – improvement of 7.95%
- Probabilistic A – improvement of 8.98%
- Probabilistic B – improvement of 8.02%
- Probabilistic C – improvement of 7.95%

In addition, in order to better quantify the improvements of Probabilistic strategies when compared to the Deterministic strategy, the graph of Figure 5, which compares only these revenues of these four strategies was created.

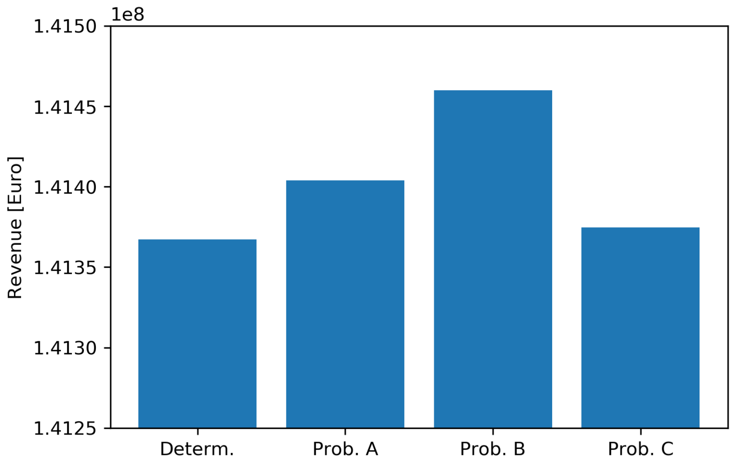

Figure 5: Comparison of revenues for strategies using probabilistic and deterministic forecast.

From Figure 4, it is possible to note that the revenues of the three Probabilistic strategies varied, and the strategy using the 24-hours profile performed the best. The improvements in relation to the Deterministic strategy were:

- Probabilistic A – improvement of 0.03%
- Probabilistic B – improvement of 0.07%
- Probabilistic C – improvement of 0.01%

Considering the results, the strategy which performed the best was the Probabilistic strategy that used the 24-hours profile to determine the optimal quantile. Figure 6 shows the accumulated revenue of the best performing strategy (green), the ideal scenario (blue) and the base strategy (orange). We can see that the Probabilistic strategy B have a revenue curve which is quite close to the ideal scenario revenue, due to its value of γ (97.08).

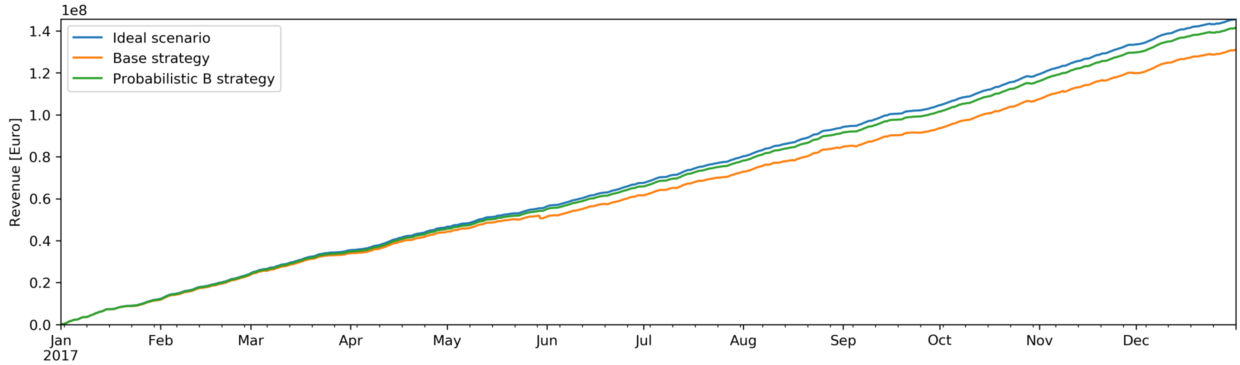

Figure 6: Accumulated revenue over the year of 2017.

4 Conclusion

Different participation strategies for renewable energy producers in the electricity market, such as wind power plants, have distinct revenue performance due to uncertainties in relation to the predictions of the amount of energy that is going to be produced. The combination of revenues of the Day-ahead market and Balancing market it is what impacts this performance.

In the investigation made in this report, the strategy which performed the best was the one using the probabilistic forecast with the optimal quantile being determined by the 24-hour profile. The performance ratio obtained for this strategy was 97.08% when compared to the ideal strategy that provides the maximum profit.

Appendices

The code used to implement the analysis in this project is provided as an Appendix and it is also available in: https://github.com/lucasblt/ren-elec-markets/tree/master/assignment2.

References

[1] Nordpool. `https://www.nordpoolgroup.com/`. Accessed: 2019-04-05.