Optimized Electricity Bidding under Price Uncertainty

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***Abstract*—This paper discusses the electricity bidding problem where the bids are based on stochastic price forecasts. The presented approach uses a simplified stochastic programming approach resulting into a mixed-integer linear programming problem. As a case study, we use a solar park with an installed battery energy storage system, the operations of which is coordinated to maximize the total profit. Our approach can solve a 6-day problem within four minutes and shows 80% optimality compared to the ground truth. It is important to be able to operate battery energy storage systems profitably in order to ensure the return on investment and – thus – sufficient capacity for stabilizing the power grid under increasing amount of variable renewable energy source.**

***Index Terms*— Battery energy storage system, Bidding, Energy market, Price uncertainties, Stochastic optimization.**

I. INTRODUCTION

Along the growing number of renewable energy source (RES) units, the volatility of power supply is increasing, and this can have unwanted effects both in reliability, as well as in electricity pricing. Especially the latter is critical to the profitability of many production processes. To guarantee grid stability, there must be sufficient resources to balance these RES-fluctuations ensuring that the demand and supply are always balanced. Demand-side management (Paulus and Borggrefe, 2011) has been the major vehicle of engaging industrial consumer in supporting the power grid stability (Zhang and Grossmann, 2016).

Some industries are also investing in battery energy storage systems (BESS) to ensure the stability of electricity supply and thus avoid unwanted disturbances that might cause process instabilities or significant losses. Nonetheless, investing in storage systems is expensive and this also adds to the operational costs. To reduce these costs there is the option to use the power storage for offering ancillary services and to participate in energy trading. This can be done for the surplus capacity and can optimally add to the profit of the system owner, also justifying the investment costs. However, participating in trading is untrivial due to the fluctuations in energy prices, which – if not well considered – may result in lost opportunities or even financial losses. Having perfect energy price forecasts would make it trivial to optimize the capacity use by a deterministic optimization approach.

Unfortunately, in real life it is close to impossible to define a perfect energy price forecast and therefore we must try to rely on, for instance, quantile price forecasts or define probabilistic scenarios expressing the uncertainty range of the expected price fluctuations. This creates a problem where uncertainty becomes one of its implicit features. There are many options to deal with optimization under uncertainty (Sahinidis, 2004) such as stochastic and robust optimization (Grossmann et al., 2016). While a rigorous multi-stage stochastic optimization problem would result in combinatorial explosion, we apply a simplified stochastic optimization approach to deal with the uncertainty space. This can be deployed for automated bidding across different markets and products and will be compared to a deterministic approach using an average forecast scenario. The comparison between these two approaches will be done using real-life price data and showing use cases of different complexities. The focus of this work lies in both the solution robustness (not violating the process or battery limits), and profit (ensuring better return-on-investment for BESS), which are both analyzed and discussed.

II. THE BIDDING PROBLEM

Electricity bidding actively brings the producers and consumers into the same table as the product price is in majority of the markets defined by the market clearing price (MCP). In an open access electricity market, the bidding problem is a complicated task because of producer's uncertain behaviors and demand fluctuation. Therefore, developing efficient and working bidding strategies is extremely important for electricity market participants to achieve the maximum profit, even more as Europe is moving towards 15-min bidding intervals for energy markets. In this paper, we consider participation in both energy and ancillary markets in an ideal scenario, i.e. without actual ancillary events occurring. This means that there are no corrective actions needed, i.e. adjustment of the BESS levels using intraday markets. In fact, here we exclude the intra-day market, the prediction of which is very difficult as it typically follows a more stock-market type of auction mechanism.

The system discussed in this paper is illustrated in Fig. 1. The renewable production may be from wind or solar and we assume a relatively reliable generation forecast, which can further be adjusted by curtailment, should it be necessary. The

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power can either be sold directly to the electricity markets or charged into a battery. In our example we assume that the only available market for RES-production is the energy markets. All ancillary service capacity must be available in the BESS, in order to ensure stability and avoid infeasibilities due to forecast errors. In short, we have three main types of decisions / transactions that must be co-optimized:

1. Sell the RES power to the energy markets or use RES production to charge the BESS – or a mixture of these.
2. Buy or sell electricity from/to the energy markets to charge or discharge the BESS.
3. Sell available energy from the BESS to the ancillary service markets – it can be in both directions to support the stability of the grid when a frequency event occurs.

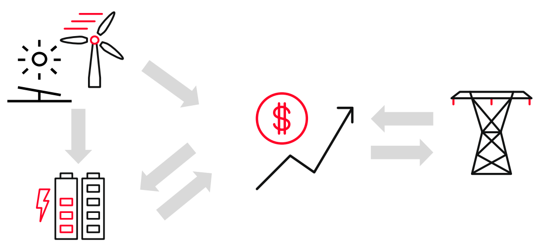

Figure 1. Example system studied with renewable and BESS

These decisions affect each other and must be done in a balanced way that maximizes the profit. In the considered example there are three markets: the typical day-ahead markets and two ancillary markets that differ from the auctioning time. All markets require bid submission between 7 to 36 hours before the start of the market day and the submitted bids should be deliverable if accepted. The acceptance or market clearance typically takes place within two hours after the bidding closure. We consider four products:

- EN: Energy (MWh)
- AS1: Ancillary regulation up (MW)
- AS2: Ancillary regulation down (MW)
- AS3: Ancillary symmetric (MW, both up and down)

Note that ancillary services are sold according to power and the services specifications define the minimum and maximum durations of the delivery. In this paper, we assume a price-taker scenario, i.e. the bids are not significantly affecting the MCP. Thus, the decision is based on price forecasting, which does not alter depending on the considered bids. Another feature considered is that accepted energy bids are always sold in full, i.e. if a bid of 5 MWh is accepted, the resulting transaction will be a delivery of 5 MWh during the specific market period mostly with a constant power level. If imbalance markets are considered it is possible to over/under deliver energy based on the imbalance prices. On the contrary, ancillary services are only delivered based on the need, which means that a 5 MW commitment (accepted bid) might result into a power injection of 1 MW for 15 minutes. Typically, the compensation is based on the MCP price and volume bid.

The main bidding problem is thus, considering the price forecasts for all relevant products, renewable energy production forecast and load forecast (a mandatory load that must be always met if it exists on site), what volumes $x_{p,m,t}$ to bid (MWh or MW) on which prices $c_{p,m,t}$ into the electricity markets m for the various products p such that we maximize the total profit and are able to commit to all accepted bids at all time points t? Here, it must be considered that the markets are sequential, i.e. if a bid into the first market to be cleared gets accepted, the corresponding energy is not anymore available for the successive markets. Thus, the most complicated problem is to optimize the first market in sequence, which must consider all future market options as well. The bids for the latter markets are typically optimized after the previous markets have already been cleared and thus can be treated as parameters (accepted bid volumes or zero for rejected bids).

Thus, as shown in Fig. 2, the target of the optimization is to find for each bid the price and volume that maximize the profit. The price directly affects the bid acceptance probability (should be equal or lower than the market clearing price) and the volume will define the feasibility as the battery limits must be respected accordingly. The pay-per-bid is another type of market but as it is becoming less popular, we ignore it in this short contribution.

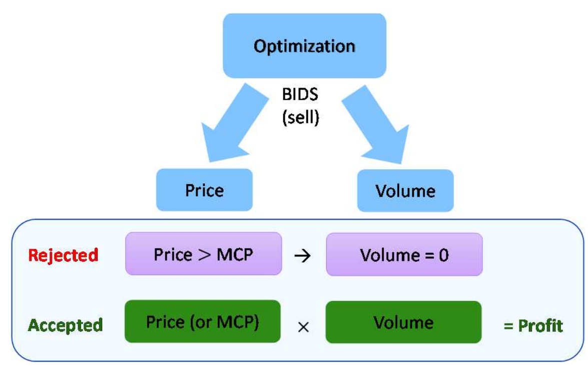

Figure 2. Logic of bid optimization and acceptance

If we have perfect knowledge of the upcoming prices, we can assume that all bids are accepted, and the problem objective can be expressed as

$$\max \sum_p \sum_m \sum_t c_{p,m,t} \cdot \left(x^{sell}_{p,m,t} - x^{buy}_{p,m,t}\right) \qquad (1)$$

In (1) the price is known and thus it is a parameter, and the problem objective remains linear. For the sequential markets, it is essential to ensure that already committed capacity for ancillary services is not compromised. All ancillary services are only sold but energy can be both sold and bought, which means that for energy products we need to split $x_{p,m,t}$ to $x^{sell}_{p,m,t}$ and $x^{buy}_{p,m,t}$, of course with opposite signs. The latter term is only applied to energy products.

The key equations to ensure are the stage of charge levels of battery B at each time point, as shown in (2).

$$B_b^{min} \leq y_{b,t} \leq B_b^{max} \quad \forall t,\ b \in B \qquad (2)$$

Since the bidding problem is often solved sequentially with some kind of rolling horizon scheme, here we assume that the final SoC at the end of the scheduling horizon should be equal to the initial conditions. This is a simple constraint to avoid that the optimization problem will deplete all available energy to profit the last time intervals on the expense of future problems. The stage of charge is maintained through the charging and discharging operations, where $\eta_{ch,b}$ and $\eta_{dc,b}$ are the respective efficiency factors. This is reflected in (3), where the dis/charging power is multiplied by the interval length Δ_t.

$$y_{b,t} = y_{b,t-1} + \left(\eta_{ch,b} \cdot x_{b,t}^{ch} - \frac{x_{b,t}^{dc}}{\eta_{dc,b}}\right) \cdot \Delta_t \quad \forall t,\ b \in B \qquad (3)$$

The studied system is shown in Fig. 3. It has a solar park connected to a BESS and can realize the energy trading illustrated in Fig. 1. In case there is special site constraints like bus limitations or similar, this can be modeled as well as a possibly load that must be satisfied. There is also a theoretical trading limit, but this is not actively considered here as it is much larger than the bus limitation.

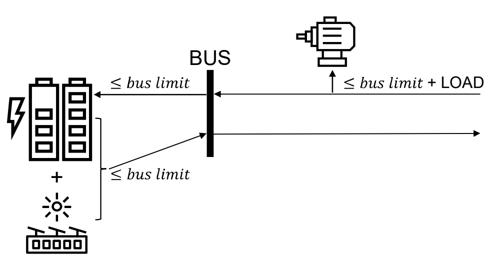

Figure 3. Setup of the studied system

At each point of time, we must maintain the energy balance shown in (4), where on the incoming side we have the renewable production X_t^{VRES}, energy we buy into the system x_t^{buy} and we discharge from the batteries. This must be equal to the load satisfied X_t^{load}, energy sold x_t^{sell} and charged into the batteries $x_{b,t}^{ch}$.

$$X_t^{VRES} \cdot \Delta_t + x_t^{buy} + \sum_{b\in B} x_{b,t}^{dc} \cdot \Delta_t = X_t^{load} \cdot \Delta_t + x_t^{sell} + \sum_{b\in B} x_{b,t}^{ch} \cdot \Delta_t \quad \forall t \qquad (4)$$

Here the variables defining the energy transactions are summed across all energy products and markets.

$$x_t^{sell} = \sum_{m\in M} \sum_{p\in P} x_{p,m,t}^{sell} \quad \forall t \qquad (5)$$

$$x_t^{buy} = \sum_{m\in M} \sum_{p\in P} x_{p,m,t}^{buy} \quad \forall t \qquad (6)$$

Having the simplified example we can solve the problem (1-6) with the slightly revised objective giving a deterministic solution, which is not realistic but can act as a global upper bound when considering uncertainty.

III. BUILDING IN THE UNCERTAINTY

Since there are no exact forecasts, the key is how to consider the uncertainty. In the previous deterministic approach, it is sufficient to bid on the actual price $c_{p,m,t}$ (or slightly lower/higher depending on the market rules). When we have built-in uncertainty, we do not actually know the MCP and must thus optimize both the bid price and volume, which makes (1) nonlinear. To account for the uncertainty we introduce scenarios, i.e. alternative forecasts with a given probability. Instead of the objective function (1) we maximize the expected profit by multiplying each objective component by the scenario probability. Ideally, the scenarios should cover the true future realization and the higher the spread around is the less accurate our scenario-based forecast is, which often results in a lower expected profit. Here, we take a similar approach as done in Kraft et al. (2023) and select a few candidate prices, which allows us to parameterize the bid prices. This was also motivated by certain markets that only allow a limited number of bid prices per day (sometimes even only one fix price). If we have a selection of bid prices, which could even be the forecasted price of each scenario at each time point – or some other statistically defined set of prices, we can preprocess them as in Kraft et al. (2023) to exclude those price levels that would be rejected for a scenario. In this paper, we use 5 price candidate levels for the ancillary services, of which only one can be submitted. These candidates are generated using the price forecasting using the min/max and average values and the standard deviation. The optimization will then select which of the selected candidates are used for bidding. For the energy, here we use the principle of self-scheduling by using two price candidate levels: one very high for purchasing and another one very low for selling energy. This is motivated as we assume a price-taker scenario, as well as acknowledge that losing an energy bid would compromise any ancillary bids since we would not be able to control the SoC-levels in advance. The objective function takes the form shown in (7).

$$\max \sum_p \sum_m \sum_t \sum_s \pi_s \cdot c_{p,m,s,t} \cdot \left(x_{p,m,s,t}^{sell} - x_{p,m,s,t}^{buy}\right) \quad (7)$$

Here, the index s refers to the scenarios and π_s is their respective probability. The sum of the probabilities of all scenarios should equal 100%. In this context, it is not possible to go through all constraints so in the following we will discuss the use cases.

The source of the forecast information is based on quantile forecasts shown in Fig. 4. Here we can see the actual spot price as a red dashed line and the corresponding quantile forecasts that were derived day-ahead.

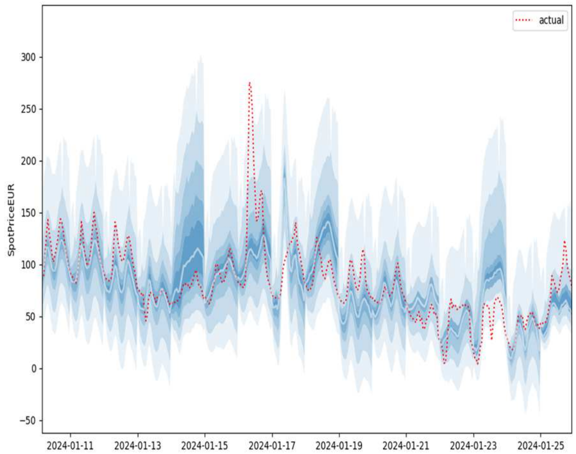

Figure 4. Example of a quantile forecasts with the energy prices

The various shadings show the different quantile levels, which mean that e.g. 30% quantile means that there is a 30% probability that the price will lie below this value. These quantile forecasts are used for creating stochastic scenarios, which indicate both price levels and their probabilities for each product, market and time interval. This can be done in many ways and since we do not have any specific restrictions, we select within which quantile we want to operate, e.g. 30-70% and create through random sampling 10 individual scenarios within these selected intervals. The example result can be seen in Fig. 5, which shows the scenarios built on the full quantile forecast (0-100%). Already the 10 scenario instances show a good coverage of the quantiles.

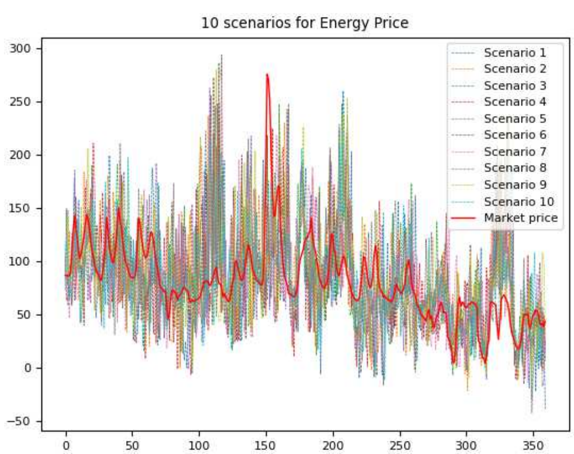

Figure 5. Example system studied with renewable and BESS

The optimization itself can be based on different number of quantiles. In general, using all quantiles (0-100%) can be expected to be very "conservative" and resulting into careful bids that are always accepted but possibly result into lower profits. On the other extreme, using only the 50% quantile (50-50%) would basically revert into a deterministic problem where the one resulting scenario has a 100% probability. Here, the forecast accuracy becomes critical since even if the bids are probably more "aggressive" many of them may be rejected, resulting into profit loss.

IV. COMPUTATIONAL RESULTS

In the following, we show the performance of various examples that comprise different quantiles. Each example is solved for a 6-day period and considers a BESS capacity of 2 MWh, which always must be kept within SoC of 10-95%. Referring to Fig. 3, the solar forecast during the studied days varies between 0 and 1.37 MW and the load is between 0.15 and 0.33 MW. We do not consider the uncertainty of these forecasts but aim at handling possible deviations using imbalance markets, which are beyond the scope of this paper. We consider only one energy market (day-ahead) and two ancillary markets with three products each. Each market is based on hourly trading intervals. We build 10 price scenarios for each valid market and product combination. This results into a relatively high combinatorial space of $10^{1+3\cdot 2=7} = 10{,}000{,}000$ scenario combinations for each time point. Should we try to model a complete stochastic tree for this we would need 240 million bidding variables per day. The bidding is done consecutively, which means in practice and first a problem considering all markets is solved in a rolling horizon manner, as in real life. After this, the market clearance takes place only for the relevant market and this fixes the bids. Next optimization takes the already fixed market as parameters and the optimization proceeds – always checking when the bidding and market clearance should take place. in other words, we simulate the "real life".

In the example we use a simplified approach and compare it with the deterministic approach, using a crystal ball or having perfection case (100% forecast accuracy) by solving the problem using the actual realized prices. This is helpful in showing the goodness of the stochastic model and how it performs. The results are shown in Table 1. The first row is the deterministic problem with the "ground truth", i.e. actual market prices and it has been highlighted through italics. We can see that the deterministic problem can be solved in less than two minutes and produces naturally a 100% acceptance ratio. Table 1 shows all experiments using different quantile selections.

TABLE I. TABLE TYPE STYLES

Quantiles	Exp. Profit	Profit	Sol. time	Accept ratio
DET	38979 €	38839 €	107	100%
0-100%	26932 €	30849 €	148	100%
10-90%	26951 €	31191 €	216	99%
20-80%	26360 €	30801 €	148	97%
30-70%	25847 €	30025 €	182	91%
40-60%	24595 €	29071 €	176	79%
50-50%	24222 €	28860 €	178	77%

From the results we can see that the best real profit (3rd column) is given by the 10-90% quantiles, which has also the highest expected profit. The solution time is also the longest but still below four minutes. Note that this is the sum of all 18 optimization runs during the 6-day period so each optimization runs should take much less than a minute. The results also show the declining acceptance ratio with reducing quantiles, which is a logical consequence of more “aggressive” bidding. Ignoring the price uncertainty and selecting the average quantile (50-50%), which can then be solved as a deterministic resulted in the worst performance with about 23% of the bids rejected.

In general, the simplified stochastic approach is in the best case able to reach a “global optimality” of around 80%. However, it must be noted that running only a six-day optimization problem cannot provide sufficient “evidence” and a basis for a reliable comparison of stochastic problems. Thus, one action item is to prepare a larger data set for comparison.

V. CONCLUSIONS

We have presented an approach for optimizing bids for electricity markets under price uncertainties. These include both energy and ancillary markets. The bidding for various products across these markets is complex as their interrelations must be carefully considered through energy balances. The results show good results indicating that with high quality forecasts we can also manage the uncertainty and stay profitable.

Further research could focus on alternative ways of embedding the quantile forecasts into the optimization, investigating optimal BESS sizing to improve the profitability, introducing intraday or imbalance markets to handle the unexpected events, such as major frequency events, inaccuracies in forecasts or SoC estimations, as well as simulating real events to test the robustness of the proposed method.

REFERENCES

I.E. Grossmann, R.M. Apap, B.A. Calfa, P. García-Herreros, and Q. Zhang (2016). Recent advances in mathematical programming techniques for the optimization of process systems under uncertainty. Computers and Chemical Engineering, 91, pp. 3-14.

E. Kraft, M. Russo, D. Keles and V. Bertsch. (2023) Stochastic optimization of trading strategies in sequential electricity markets, European Journal of Operational Research, 308 (1), pp. 400 – 421.

M. Paulus, F. Borggrefe (2011). ”The potential of demand-side management in energy-intensive industries for electricity markets in Germany. *Applied Energy*, 88 (2), pp. 432 - 441.

N.V. Sahinidis (2004). Optimization under uncertainty: State-of-the-art and opportunities. Computers and Chemical Engineering, 28 (6-7), pp. 971-983.

Q. Zhang and I.E. Grossmann (2016). Enterprise-wide optimization for industrial demand side management: Fundamentals, advances, and perspectives. Chemical Engineering Research and Design, 116, pp. 114-131.