Rolling Horizon Simulator for Evaluation of Bidding Strategies for Reservoir Hydro

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***Abstract*—In this paper, a practical approach for benchmarking different bidding strategies towards the day-ahead market has been evaluated. A rolling horizon simulation framework is developed and closely integrated in the daily operations of a hydropower producer. The power producer's existing framework of decision support models and data for prices and inflow has been used to simulate the use of alternative strategies on a real life case. In the simulation procedure, a mixed-integer stochastic optimization model is used to determine the bids to the electricity market and the production schedule.**

It has been demonstrated that simulation over a long time-horizon can be used to evaluate different bidding strategies. Results from the case study show that one single strategy not necessarily will be the optimal one under all conditions, because the optimal strategy will depend on the the state of the system.

***Index Terms*—Hydropower, Bidding problem, Day-ahead market, Rolling Horizon Simulator**

I. INTRODUCTION

In modern power systems, electricity is traded on various markets. For individual power producers, the trading strategy should optimize the value of resources in a long and short-term perspective [1]. To manage and plan for sales in the electricity market, most power producers have engaged production planners who combine decision support models with commercial competence and experience to determine the daily bidding strategy.

As bids for the market must be based on physically feasible production schedules, optimization models used for bidding must consider the production system as well as market aspects such as expectations of future market prices. For hydropower producers with reservoir storage, there is also uncertainty in future inflows. Accounting for these uncertainties is crucial in long and medium-term hydropower scheduling, but it might also be beneficial to consider them in the bidding process, i.e. in the daily scheduling process. Such stochastic models have been formulated in the literature [2]–[4] , but have not yet been implemented in any significant extent in the industry.

Presently, the main strategies implemented by Nordic hydro-power producers for bidding towards the day-ahead market are based on deterministic models, and are described in [5]. Optimal bidding strategies, also referred to as optimal offer construction in electricity markets, have also been investigated for other liberalized electricity markets [6].

With the introduction of multiple markets with different closure times, the hydro-power producers also have the option to bid and allocate production to markets where they believe the highest profit can be obtained. The optimization of sequential markets have been the topic for several publications, and bidding strategies are often grouped into sequential or coordinated bidding strategies [7], [8].

Finally, with the increasing flexibility among consumers, estimating the value of bidding strategies from a consumer point of view have also received increased attention [9].

II. PROBLEM FORMULATION

Before deciding to implement new operation and bidding strategies in the existing decision support system, power producers need to evaluate the performance of alternative strategies.

Gains from improved modeling could either be documented by theoretical analyses, or be verified by comparing the performance of different strategies over time. In [5], comparison between four different bidding strategies in the day-ahead market were investigated for a limited number of days. In [10], back-testing of a stochastic coordinated bidding model for sequential electricity markets was investigated over a time horizon of 200 days.

To capture the dynamics and large variations in prices and inflow, it is necessary to evaluate performance over a longer time horizon. When long-term simulations are combined with historic forecast for prices and inflow that were available to the planner at that time, it is possible to estimate accurately the consequences of choosing one strategy over another. The long-term aspects of the trading strategy are important due to the ability to store water (energy) in reservoirs. Access to historic water values is therefore also important. The water value can be defined as the future expected value of the stored marginal kWh of water, i.e. its alternative cost [11], [12].

A. *Bidding strategies*

Two strategies have been evaluated in this analysis. The first is *Bidding the expected volume*. The expected volumes are found by deterministic optimization against forecasted price and inflow using the SHOP software, and are submitted as fixed hourly bids to the power exchange. SHOP is a software tool for optimal short-term hydropower scheduling developed by SINTEF Energy Research, used by many hydropower producers in the Nordic market [13].

The second strategy is *Stochastic bidding*. The stochastic model is based on the deterministic method, but allows for a stochastic representation of inflow to the reservoir and day-ahead market prices. In this case, bid-curves can be generated from stochastic model as described in [14]. The bid-curves can be represented as a bid-matrix sent to the power exchange prior to the operation day. For hourly bids, the matrix consist of one row for each hour, and columns for each price point. Graphically, bids for one day can be illustrated as in Fig. 1. In this work, we assume that the producer is a price-taker and the committed volumes will be calculated by linear interpolation using the realized market price in the market clearing. When spot prices are available, resulting production for each power station can be calculated. The resulting production is plotted for a selected date in the simulation period with bid-curves and realized spot prices in Fig. 1. Detailed production is given in Table II in Appendix.

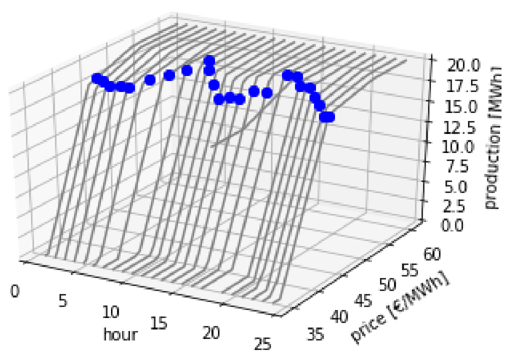

Fig. 1: Bid curves for one investigated power-plant, on date[i] Dec 2018. Resulting production is shown with round markers

Two important observations can be made for the bid curves in Fig. 1. The first is that even for the same day, where realized prices for one hour is equal to another hour, the resulting production will not necessarily be the same. As an example, a price 46.3 € in hour 1 would give a production of 18.5 MW, the same price in hour 9 will only give a production of 13.3 MW. This is because the bid curves are different for the two hours, so interpolation between the market price and the bid curves will result in different realized volumes. To understand why the bid curves are different, we have to look at the price scenarios in Fig. 2 associated with generation of the bid-curves.

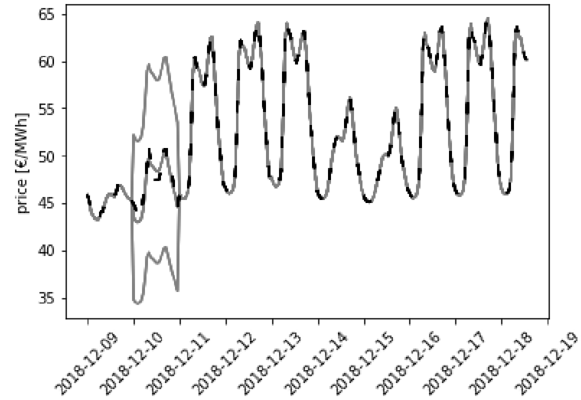

Fig. 2: Price scenarios for date[i] Dec 2018. Realized price is dashed line

While a price of 46.3 € in hour 1 is well above the expected price for this hour, it is below the expected price for hour 9. In hour 1, interpolation will therefore be between volumes associated with the high- and expected price scenario. Both of these scenarios give close to full production in hour 1, which again is a result of prices for both scenarios being above the water value. In hour 9, interpolation will be between the low- and expected price scenario. The low scenario has zero production in hour 9 since the price is below the water value. Including more scenarios with prices close to the water value could reduce the difference in production that is observed for similar prices, but would also increase calculation time.

Another observation is that the bid-curves only span out for a limited region. This is do to the fact that the minimum and maximum bid price is set by the minimum and maximum prices in the price scenarios. This do not represent a problem as long as realized prices remain within the min and max values. However, if prices turn out to be outside this limits, it is important to have a strategy to handle this situation. If a linear interpolation between 0 €/MWh and the minimum value is chosen in a situation where there is a risk of flooding, this could lead to unnecessary flooding. An alternative strategy in this situation is to maintain the same production for all prices down to 0 €/MWh, as the production associated with the minimum price in the price scenarios. This however, could lead to a sub-optimal solution if we were to experience a collapse in prices without any risk of flooding. Another alternative could be to include scenarios with very high and very low prices, even though estimating probabilities for extreme scenarios could be difficult, and calculation time would increase.

B. *Evaluation method for a single day*

There exist several methods to evaluate the performance of a bidding method. In this paper we compare cost and revenues obtained from producing according to the cost minimizing schedule that cover the commitments for the two bidding methods. This value (Π) is further compared to an optimal solution where we assume perfect foresight for price and inflow. The perfect foresight model therefore represent the maximum value that can be obtained for a specific day.

For each selected bidding strategy, we obtain an hourly volume commitment for the day-ahead production. After market clearing, when prices for the next day are known, the production schedules are re-optimized in the after spot problem. To take into account the possibility for interacting with the intraday market, there is a possibility to deviate from the committed load with a pre-defined penalty of 5 EUR/MW. This represents an estimate for the average cost the power-producer would experience for trading after market clearing, however the cost could vary significantly. Including an intra-day market with actual historic prices has not been in the scope for this analysis, but could be a topic for further research. We further assume that bidding is performed close to midnight, and that information about inflow for the next day is known when re-optimization is conducted. To link the short term optimization with long term water values, and to capture the possible trade-off between deviating from the day-ahead plan with producing more or less the remaining week, the optimization is conducted for a whole week.

The linear optimization problem in SHOP is designed to minimize the cost in a hydro scheduling problem. The objective function is used to measure the sum of all costs, income and penalties. It is tempting to use this as a measure for value, but in a successive linear optimization problem where penalties are involved, penalties obtained in the early iterations are not necessarily passed on to the last iterations. A detailed accounting follow-up system which measures all incomes, unbalance- and start-up- cost as well as the value of water in the reservoir is an alternative way to establish a basis for comparison.

Symbol	Explanation
Variables	
Π_s	Total measure for value from strategy s [€]
I_h	Income for the simulation in hour h [€]
U_h	Unbalance cost in hour h [€]
S_h	Start-up cost in hour h [€]
R_h	Value of stored water in reservoir r at the end of the simulation period [€]
λ_h	Market price in hour h [€/MWh]
P_h	Total production in hour h [MWh]
μ_h	Number of generators starting in hour h
$P^{com}_{h_g}$	Committed volume for generator g in hour h
$P^{plan}_{h_g}$	Re-optimized production plan for generator g in hour h
Parameters	
S^{cost}	Start-up cost for each generator [100 €]
C^{dev}	Cost for deviating from plan [5 €/MWh]

The total performance-gap (β_s) for a select strategy is calculated as the difference between the optimum value for the relevant bidding date and the value of the investigated strategy. A high number for (β_s) indicate poor performance.

$$\beta_s = \Pi_{opt} - \Pi_s, \tag{1}$$

$$\Pi_s = \sum_{h=1}^{168} (I_h - U_h - S_h) + \sum_r R_r, \tag{2}$$

$$I_h = \lambda_h \cdot P_h, \tag{3}$$

$$U_h = C^{dev} \cdot \sum_g \left| \left(P^{com}_{h_g} - P^{plan}_{h_g} \right) \right|, \tag{4}$$

$$S_i = \mu_i \cdot \ S^{cost}, \tag{5}$$

C. Long term simulation

The main objective of the analysis is evaluate the performance of different bidding strategies. To simulate the performance over a longer time horizon, a simulation framework as illustrated in Fig 3 has been developed in Python. In the analysis, every simulated day starts with the historical reservoir filling for that day, and historical data for reservoir filling, inflow and prices are collected from the production database.

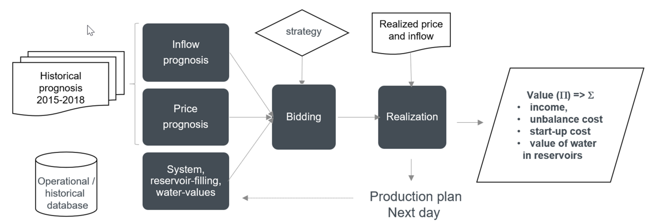

Fig. 3: simulation framework for long-term evaluation of bidding performance

D. Quality assurance

When investigating the performance of a limited number of days, it is possible to manually review the results to ensure that they seem reasonable by looking at production plans and reservoir development. However, when simulating over a longer time horizon such as years, there is a need to implement some automatic quality assurance calculations that can help to consider whether the results are reasonable or not.

Two simple measures have been implemented in the simulator to check the validity of the results. They define the upper and lower limit for performance of the investigated day. Results for a strategy where we have imposed restrictions on the day-ahead production should never be able to perform better than the optimal plan with perfect foresight on prices and inflow, and full freedom to allocate production. The lower limit is defined by :

$$\Pi_{optimal} - \Pi_s >= 0, \tag{6}$$

This follows the general rule that when adding constraints to an optimization problem, the new optimal solution should always have a lower or equal objective value.

An interesting observation here is that if we change the simulator to update the daily initial reservoir levels for each strategy based on results from the previous day, this would not necessarily be the case. When the simulator is updated with individual reservoir levels, each strategy will follow their own reservoir trajectory . A consequence of this is that what might seem as an optimal decision today, might not necessarily be an optimal solution if long term prices and inflow turn out to deviate much from the expectations.

A penalty cost for changing the production plan has been introduced. With this option, the model will always have the possibility to adjust the production for day-ahead to the production given by the optimal plan where prices and inflow are known prior to bidding. The performance of a strategy should therefore never be worse than the cost of changing the plan to optimal production. The upper limit is therefore defined by:

$$\eta_s <= C^{dev} \cdot \sum_{g} \sum_{h=1}^{168} \left| \left(P_{h_g}^{optimal} - P_{h_g}^{plan} \right) \right|, \tag{7}$$

III. Case study

A. System description

The river system analyzed in this article is a section of a river system located in south-western Norway. The investigated system consists of three linked reservoirs. Water is drawn from the upstream reservoir to two plants in series with a small reservoir in between. The discharge capacity [m3/s] for the lower plant is 10 % higher than for the upper plant. There is high head loss in the lower plant, and there is time-delay between the different reservoirs. The system has a high utilization rate, and is sensitive to flooding in periods with high inflow. Finally, there could be gains from head-optimization in the system motivating high water level in the intake reservoirs, which again could increase the risk of flooding.

B. Model input

a) Price: The input price for the simulator is based on the price-prognosis for the NO2 NordPool area from the power producer's short-term market model. Historical prognosis are imported and pre-processed in the simulator. Only the expected price is available for the investigated time period. It has therefore been necessary to synthetically generate a sample space for the stochastic optimization. In this analysis three scenarios are used. The scenarios represent the expected value (E) and a high (H) and low case (L) with the probabilities given in Table I.

The prices are only spread out for the next day, and after day-ahead the expected price is used for all scenarios, as illustrated in Fig. 2. Water-value are in general lower than prices in this investigated period.

b) Inflow: The input to the inflow model is based on historical observations (1958-2011) with weekly resolution. A model with finer resolution exists in the operational environment, but historical prognosis from this model has not been recorded. Three inflow scenarios are used, and sample space for next bidding day is selected as the average (A), 25 and 75 percentile. Equal probability has been given for all inflow scenarios. Realized inflow has been collected from the operational database.

c) Stochastic representation: With three prices and three inflow scenarios, the probability matrix with nine scenarios used for the stochastic bidding is given in Table I.

TABLE I: Probability matrix for price and inflow

			Inflow		
	Scenario		IA	I25	I75
		Probability	1/3	1/3	1/3
Price	PE	1/2	S1 1/6	S2 1/6	S3 1/6
	PL	1/4	S4 1/12	S5 1/12	S6 1/12
	PH	1/4	S7 1/12	S8 1/12	S9 1/12

When applying stochastic optimization, it is important to be able to represent the uncertainty in prices and inflow in the best way. Several methods exists, where the use of scenario-trees is one that is commonly applied in Hydro Scheduling problems. This is not a trivial task and has been a topic for research in several publications [15]–[17].

Even though a theoretically robust way to implement a stochastic bidding model could be to focus on correct representation of input parameters such as inflow and price, this is not the target of this analysis. A simplified approach is chosen for representation of uncertainty, and the main objective is to demonstrate a method of how to compare two different bidding strategies.

Even though a simplified approach to represent uncertainty is chosen, it might still represent a realistic alternative for power producers. Given the focus many companies have on producing an up-to-date forecast for prices and inflow close to the bidding deadline, it might not always be possible to span out a samples space with correct probabilities for prices and inflow. There would simply not be sufficient time to re-run price and inflow models when a market analyst or hydrologist decide to change the expected forecast close to bidding deadline. The question addressed in this analysis is if a power producer which today is bidding deterministic, would obtain increased value over time by applying a stochastic optimization model with nine scenarios as given in Table I.

IV. Results

Simulation for the two investigated bidding strategies have been conducted for the year 2018. Fig. 4 gives a summary of results from one year of simulation. The 365 markers represents the strategy with the lowest deviation from optimum for that day. If the marker is round, deterministic bidding is optimum that specific day, for triangular markers, stochastic bidding is best. The two strategies have been separated by the horizontal-axis to get a better overview of the amount and distribution of samples for each strategy. Values on both sides of axis are positive, since we in both cases are measuring the absolute loss compared to an optimal plan.

An interesting observation is that during the first 3-4 months of 2018, the deviation from optimum plan is very small both

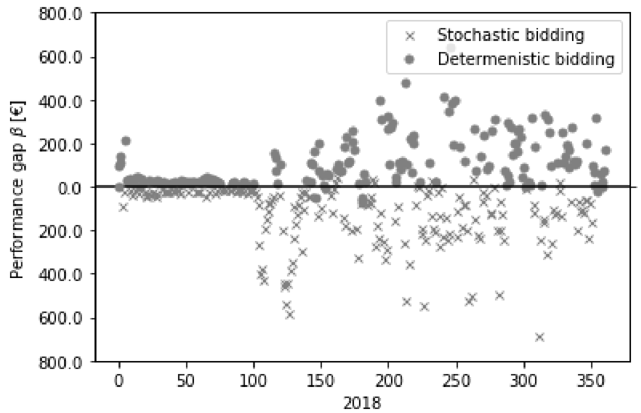

Fig. 4: Performance-gap 2018. Lost value relative to optimum for deterministic and stochastic bidding

for the deterministic and stochastic bidding strategy. This can be explained by the low water values that can be observed during this period. The water values are considerably lower than the market prices, giving a strong production signal and more or less equal production plans for all strategies as well as for the optimal plan. By the end of March, water values have increased considerably and are much closer to the market price. This makes the decision whether produce or not more complex, and the risk of deviating from optimal plan is increasing.

The results show that bidding the expected value turns out to be best in 175 days (47 %) of the cases, while stochastic bidding turn out to be best in the remaining 190 days (53 %)

Since we are measuring the lost value compared to an optimal bidding strategy where day-ahead prices and inflow are known prior to bidding, it is possible to calculate the total expected loss over a time period compared to optimal bidding. For deterministic bidding this turns out to be 62,000 € (0.65 % of 2018 income), while it is 56,000 € (0.59 % of 2018 income) for stochastic bidding. It is important to realize that the investigated river system had a very high utilization rate during 2018, and that the limited degree of flexibility reflects the fairly low deviation from optimum. However, even a minor difference of 0.06 % could have a significant impact on profitability for for a Hydro power-producer if the method proves to be generally applicable for a wider range of river-systems.

Even though there is a fairly equal split between the number of days when the two strategies are preferred, choosing a stochastic strategy will give a significant lower loss compared to optimum over the time span of one year. When investigating the daily losses for each strategy, it can be observed that deterministic bidding is over-represented in the group where losses compared to optimum is above 600 €/day. Further investigation of periods where these situations are represented, show that several of these occur in the spring during April-May. Detailed results for this period can be found in Fig. 5 in the Appendix. The spring period when snow-melting has started, is a period with generally higher inflow in the Nordic region, and also larger volatility in the inflow compared to the winter.

The inflow forecast to the model is based on historical observations, and when the actual inflow deviate from the forecast, the stochastic models will outperform the deterministic model. Improved forecasting techniques which already are implemented for the existing river-system will improve performance of the deterministic models, while increasing volatility both related to prices and inflow might favour stochastic models.

V. Conclusion

It has been demonstrated that simulation over a long time-horizon can be used to evaluate different bidding strategies. Evaluation on a real life case study show that if one strategy is to be chosen for that specific system for all bidding days, a stochastic model would be preferred since this has the lowest total deviation from optimal over time. However, one single strategy will not necessarily be the optimal one under all conditions, because the optimal strategy will depend on the state of the system. Typically, when realized prices or inflow deviate considerably from expectations, there would be a benefit of choosing a stochastic bidding strategy. However, for almost half of the investigated days, using a a fixed factor to span out the sample space for price and inflow scenario result in lower value for the stochastic model since the stochastic model would be to risk-averse in situations when price and inflow realize close to expectations.

The upper limit for the performance gap for each strategy is directly linked to the penalty of 5 EUR/MW used in this analysis. Including an intra-day market with actual historic prices would give an improved estimate for the actual performance-gap for the power producer, and could be a topic for further research.

There are few alternative to stochastic bidding if one wish to take into account inflow uncertainty in the bidding process. However, several other strategies can be chosen for handling price uncertainty. Multi-deterministic bidding or bidding according to marginal cost [5] are two methods that would be interesting to test within the simulation framework described in this paper.

The simple measure of performance-gap implemented in this paper makes it possible to compare a wide range of bidding strategies. Even though the simulation process is time consuming, the resulting performance-gap can easily be stored together with important input parameters for further analysis. One such analysis is to evaluate if it is possible to predict in advance which model should be chosen under certain conditions. This will be a research topic for further improvement.

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VI. Appendix

TABLE II: Resulting production with bid-curves and spot-prices as illustrated in Fig 1 and Fig 2

Hour	Price €/MWh	Production MWh
1	44.9	18.2
2	44.4	18.3
3	43.8	18.1
4	43.8	18.3
5	43.5	18.3
6	45.5	19
7	47.4	19
8	48.8	19.4
9	51.2	20.1
10	49.2	19.8
11	48.2	18.5
12	47.4	17.3
13	47.4	17.7
14	47.4	17.7
15	48.1	18.7
16	48.7	18.4
17	50.6	20.1
18	50.7	20.1
19	49.1	19.8
20	49	19.7
21	48.1	19.1
22	46.9	18.9
23	45.6	18.1
24	44.5	18.8

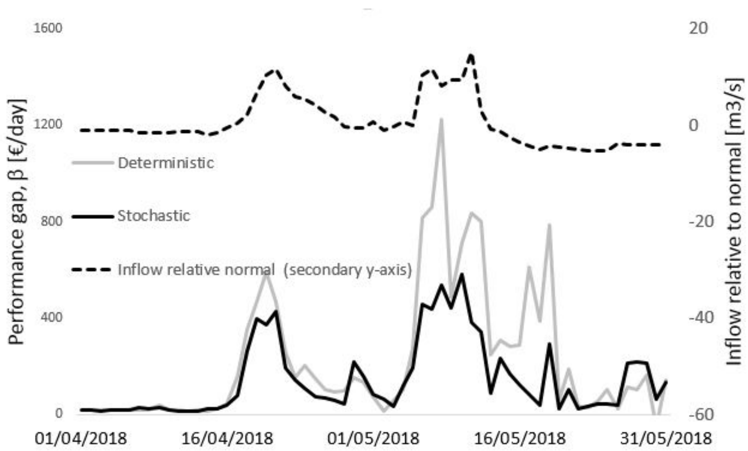

Fig. 5: Detailed results for April and May 2018, including inflow relative to normal