Coordinated optimization of weekly reserve, day-ahead and balancing energy trade in hydropower

Marte Fodstad[1], Eirik Schou Grytli[2] and Magnus Korpås[2]

[1] SINTEF Energy Research, Post box 4761 Sluppen, N-7465 Trondheim, Norway
[2] Norwegian University of Science and Technology, Dept. of Electric Power Engineering, N-7491 Trondheim, Norway

E-mail: `Marte.Fodstad@sintef.no`

Abstract. We present a model for optimal trade in a weekly power reserve market under day-ahead and balancing market price uncertainty. The model takes the perspective of a price-taking hydropower producer and a case study for the Norwegian market design and a Norwegian multi-reservoir water course for a winter week is presented. We demonstrate how a bid curve for the reserve market can be established through a sensitivity analysis on reserve prices, and observe that the optimal trade in the succeeding day-ahead and balancing market is highly sensitive to the reserve obligation.

1. Introduction

Ever since deregulation of the electricity market, the day-ahead market has been the main market in short-term bidding and scheduling. While day-ahead still being by far the largest market, an increasing focus has the last years been given to other short-term markets, such as reserve and balancing markets. This is usually motivated by increasing variability in the power system due to the introduction of more intermittent production.

There is a large research literature on short-term bidding and scheduling in hydropower production, see [1] for a survey. The day-ahead[1] bidding and scheduling problems are tightly linked since the production cost is dominated by the opportunity cost of the water. Also trading of reserve capacity and balancing energy are dependent on the day-ahead bidding and scheduling, since delivery of these services utilizes the same production system as day-ahead delivery. Several papers look into the coordinated optimization of multiple sequential markets. For instance [2] reviews literature on day-ahead, intraday and balancing market trading, but points out that the literature is incomplete and few results show substantial gain in coordinated bidding as opposed to bidding in the markets separately. Also [3] find a limited value of coordinated bidding in the day-ahead and the balancing market, but points out that this might increase as the renewable intermittent production increases causing the value of balancing energy to increase. While [2] and [3] discuss energy markets with different timing, [4, 5] combine bidding in the secondary reserve market trading reserve capacity, the day-ahead market and the intraday market. In a case study they observe less aggressive day-ahead trade and an increased expected profit for a hydro-thermal producer conducting coordinated bidding in the three markets relative to day-ahead trading only.

[1] In literature 'day-ahead' is usually not stated explicitly when referring to this model class.

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We present a short-term stochastic programming model for coordinated trading in three markets, the reserve market (RKOM), the day-ahead market (DA) and the balancing market (BM). The model follows the Norwegian market design and a case study for a Norwegian hydropower producer is presented. In the next section the model with data for the case study is presented. In Section 3 the results are presented and discussed before some concluding remarks are given in the last section.

2. Model and data description

We use a stochastic mixed integer program [6] representing a one week horizon with hourly resolution in this work. It is an extension of the one-day model described in [7] with further details given in [8]. In the following we give a short description of the model, emphasizing the model extensions.

2.1. Model description

The model represents three markets, the balancing market (BM), the day-ahead market (DA) and the reserve market RKOM. BM is the tertiary energy reserve market for both up and down regulation, which is traded on an hourly basis and cleared real-time. Remuneration in BM is according to the activated energy. DA is an energy market with hourly resolution and it is cleared the day-ahead. RKOM is a reserve market that is established by the Norwegian TSO to make sure sufficient up-regulation capacity is made available in BM. It is cleared the week before operation for two time blocks; night (00-05 Monday-Sunday) and day (05-24 Monday-Sunday), where only the day-block is included in the model due to limited data availability. A RKOM contract commits the bidder to reserve the offered capacity and bid it in the BM market. [9] Since no pump-capacity or fixed delivery obligations are modelled, the producer can sell, but not buy in the DA market. The modelled producer is a price-taker in all markets.

The markets are represented in a multi-stage scenario tree with 15 stages, each stage having a 24 hour resolution. An illustration of the first day is given in Figure 1, and for each of the remaining six days stages similar to the two last in Figure 1 is added. In the stages where DA is cleared the scenario tree contains DA prices, in the stages with BM activation there are BM prices, and in the first stage a deterministic RKOM price is given. Activation of upward balancing energy is assumed whenever the BM price exceeds the DA price, and visa versa for downward regulation. To reduce the computational burden all BM bids are in one stage, rather than 24 stages that would better reflect the hourly bidding.

The bidding in DA and BM is modelled as in [3] with bidding variables, $x^{m}_{b,t,s}$, cleared obligations $y^{m}_{t,s}$ and predefined bid price points $b \in 1 \dots B$. Here $t \in \mathcal{T}^{\mathrm{RKOM}}$ is the hour from the set of hours in the RKOM day block, $s \in \mathcal{S}$ is the scenario and $m \in \{\mathrm{DA, BM\text{-}, BM\text{+}}\}$ is the market, either DA, BM down-regulation or BM up-regulation. In RKOM the price, P^{RKOM} is assumed known, and the model optimizes the reserve capacity, y^{RKOM}. The capacity reserved for RKOM cannot be sold in DA, which is enforced in Eq. (1). $\overline{Q}$ is the maximum production capacity. Further, the reserved capacity should be offered in the BM market, which implies that the BM bid for the highest bid price at least should be equal to the reservation, as in Eq. (2). The RKOM income, $P^{\mathrm{RKOM}}y^{\mathrm{RKOM}}$, is added to the objective function.

$$y^{\mathrm{DA}}_{t,s} \leq \overline{Q} - y^{\mathrm{RKOM}} \qquad , t \in \mathcal{T}^{\mathrm{RKOM}}, s \in \mathcal{S} \tag{1}$$

$$x^{\mathrm{BM+}}_{B,t,s} \geq y^{\mathrm{RKOM}} \qquad , t \in \mathcal{T}^{\mathrm{RKOM}}, s \in \mathcal{S} \tag{2}$$

The production system used in this study is a Norwegian cascade with 11 reservoirs and 14 generators, with a overall storage capacity of 1332 Mm^3 and a production capacity of 990 MW. The production functions are piecewise linear and concave, and the water head is assumed

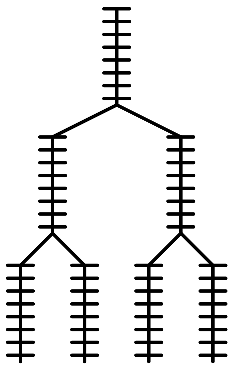

Figure 1. Illustration of the stage structure for the first day. The illustration shows a small scenario tree with two scenarios in each branching. For simplicity only eight hours are illustrated per day.

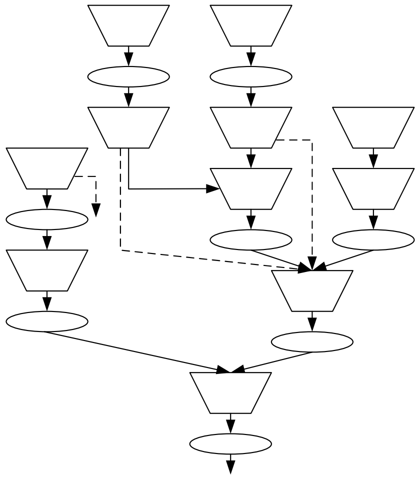

Figure 2. The production system. Trapezoids are reservoirs, ellipsoids are plants, arrows are flows while dashed arrows are spillage or bypass when deviating from the regular water way.

constant. The start/stop of generators is represented with binary variables with related start-up costs and minimum production levels. Between the reservoirs there are water ways for discharge, spillage and bypass with pre-set time delay and minimum and maximum limitations. The marginal water values, which represents the opportunity cost of water, is represented by a set of multi-dimensional linear cuts calculated by a medium-term scheduling model [10]. The case study represent a winter week, with initial level of 75% for all reservoirs. Price scenarios are generated from historical prices for price area NO2 in Norway during the winter of 2014, with an average DA price at 33.7 €/MWh, see [11] for a description of the scenario tree generation procedure. The model is tested for 12 RKOM prices in the range 0.6-13.7 €/MW, all prices within the range of observed prices for the last three years.

3. Results

We focus the case study on how variation in the RKOM price affects the position in the different markets and the overall operation of the production system. The results provide an example of realistic trades and operations, but are dependent on the given DA and BM prices in the scenario tree, and are not necessarily valid for an other scenario tree. Figure 3 shows how the individual components of the objective function change with increasing RKOM price. The overall objective value and RKOM income are increasing, which should be expected, while the income from DA is decreasing. This decrease is due to the required reservation of capacity, but the whole loss in DA is not offset by the increased RKOM income. Parts of the loss is compensated by an increasing BM income since the reserved capacity is offered for up-regulation in BM. Since up-regulation is only activated approximately half the time, the water consumption is reduced when DA trade is replaced with BM trade. This can be seen by the increase in 'Change in EFI' (expected future income), which represents the changed expected value of the stored water from the beginning to the end of the model horizon. The negative values indicate that the production during the week is larger than the inflow, which is typical in the winter season in Norway.

The optimal capacity reservation in RKOM for increasing RKOM prices is presented in Figure 4. This corresponds to the optimal bid curve for this production system for the given week of study and the given RKOM prices. It shows how the model stays out of the RKOM

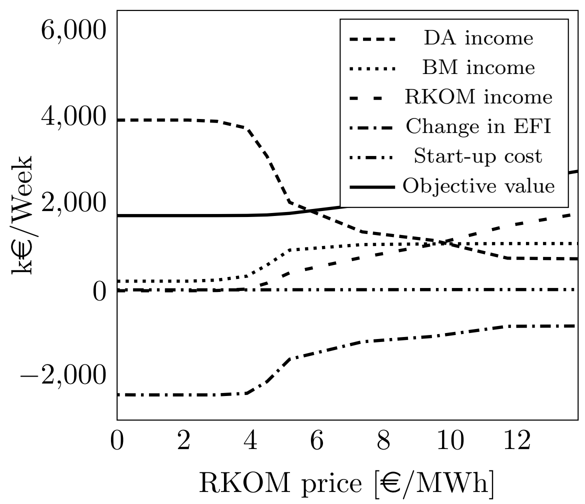

Figure 3. Objective function value for different RKOM prices

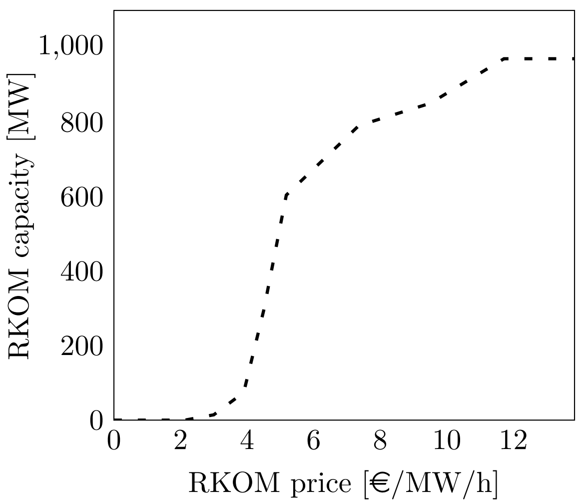

Figure 4. RKOM bid curve given by optimized capacity for different RKOM prices

market at very low prices, and monotonically increases until almost all capacity is offered to the RKOM market at high prices. In real life the higher levels are unlikely to be reached when clearing the RKOM market, since the capacity is more than twice the largest total amount observed in the market the last two years. Still this does not invalidating the bidding curve which for a price taker represents the expected marginal cost of delivering the service.

The expected marginal cost is dominated by the opportunity cost as the only direct cost, the start-up cost, is very small relative to values achieved in the markets, as seen in Figure 3. In the multi-market situation described in this model, the opportunity cost is defined by the combination of trades in DA and BM and the water value representing the storing of water for later weeks. The market rules and production system, as modelled in Eq. (1)-(2), makes the sources for opportunity cost dependent on each other, which causes the optimal position in each market to change as the RKOM position changes. This is illustrated in Figure 5 where expected DA, BM up- and BM down-regulation dispatch volumes as a function of RKOM price is given. As previously observed we see how the DA volume and the total dispatch is reduced as the RKOM price increases. Further, it can be observed that the amount of BM down-regulation is reduced, since down-regulation cannot exceed the DA position. On the other hand, the BM up-regulation is relatively stable over the whole RKOM price range, which is surprising taking into account that the aim of the RKOM market is to secure sufficient BM up-regulation capacity. Zooming in on the expected BM up-regulation dispatch in Figure 6 it shows that the BM up-regulation is decreasing in parts of the RKOM region. A possible explanation for this non-obvious result is that a small DA commitment, due to reserving the capacity in RKOM, requires stopping some generators, and the cost of restarting the generator to provide up-regulation reduces the BM up-regulation bid and thereby the activation of up-regulation for the hydropower producer. This study shows the situation from a single price-taking producer's perspective, while in a market perspective where the need for up-regulation is inelastic and if multiple producers observe the same incentive, this phenomenon could cause the BM price to be higher at a high RKOM price than at a low RKOM price all other equal.

4. Concluding remarks

We have presented a model for optimizing a hydropower producer's trade in three markets; the weekly reserve market (RKOM), the day-ahead market and the balancing energy market. The

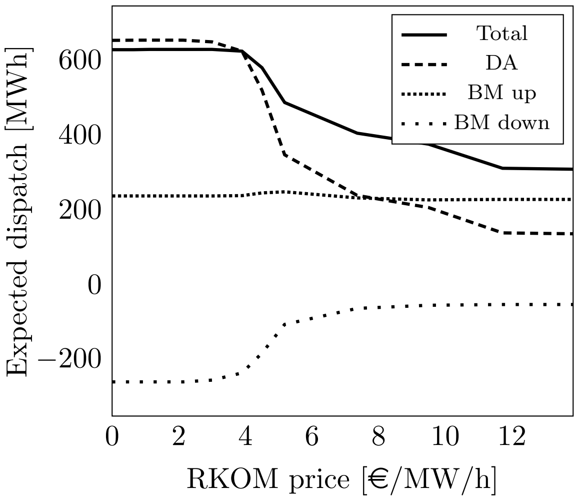

Figure 5. Expected DA and BM dispatch volume for different RKOM prices

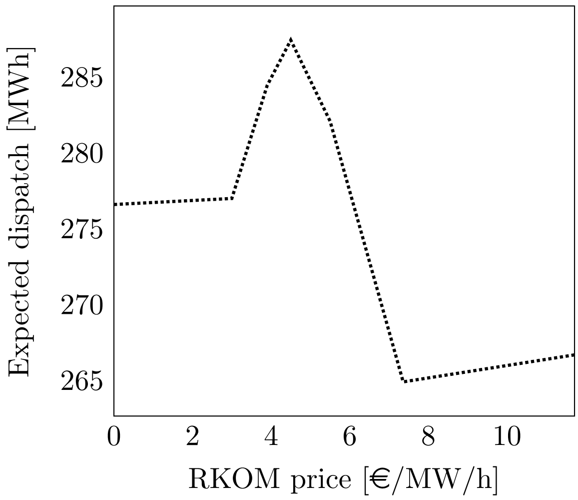

Figure 6. Expected up-regulation dispatch for different RKOM prices

market modeling follows the Norwegian market design. It is illustrated how a sensitivity study on the RKOM price can be used to produce a bid curve for the RKOM market. A case study for a Norwegian producer in a winter week is presented. The results show that both operation and trade in the day-ahead and balancing down-regulation market significantly change as the price and quantity in RKOM change, which supports the usefulness of model-based decision support for RKOM bidding. Further, the study show that for the given day-ahead and balancing market prices the balancing market up-regulation dispatch only moderately changes as the RKOM price and quantity increase, and that the changes are negative in parts of the RKOM price range. This is a surprising observation that should be studied further, since the objective of the RKOM market is to secure sufficient amount of upward balancing energy.

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