Multi market bidding strategies for demand side flexibility aggregators in electricity markets

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Abstract

Due to the electricity systems' increasing need for flexibility, demand side flexibility aggregation becomes more important. An issue is how to make such activities profitable, which may be obtained by selling flexibility in multiple markets. A challenge is to allocate volumes to the different markets in an optimal way, which motivates the need for advanced decision support models. In this paper, we propose a methodology for optimal bidding for a flexibility aggregator participating in three sequential markets. We demonstrate the approach in a generalized market design that includes an options market for flexibility reservation, a spot market for day-ahead or shorter and a flexibility market for near real-time dispatch. Since the bidding decisions are made sequentially and the price information is gradually revealed, we formulate the decision models as multi-stage stochastic programs and generate scenarios for the possible realizations of prices. We illustrate the application of the models in a realistic case study in cooperation with four industrial companies and one aggregator. We quantify and discuss the value of flexibility and find that our proposed models are able to capture most of the potential value, except for some extreme cases. The value of aggregation is quantified to 3 %.

Keywords: Demand side flexibility, Aggregator, Multi Market Bidding, Smart Grids, Stochastic programming

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1. Introduction

Due to the growing share of intermittent generators connected at various voltage levels, electrification of the transport sector and the development of new consumption patterns, the electricity systems face an increased need for flexibility [1]–[3]. Eurelectric defines flexibility as "*the modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) in order to provide a service within the energy system*". Since most of the above-mentioned changes come at the distribution grid level, the flexibility is in particular needed at the demand side.

In order to exploit the flexibility potential of smaller customers, the concept of aggregation is important [1]. A flexibility aggregator is an entity that pools small volumes of flexibility and acts as an intermediary between providers and procurers of this flexibility. Moreover, the flexibility aggregator makes market access possible for demand side flexibility, by reducing transaction costs and pooling small volumes to large enough for market participation. However, an issue to be addressed is how to make a profitable business case for a flexibility aggregator. One possible approach is to sell the aggregated demand side flexibility in multiple markets, and hence create multiple revenue streams.

Also ENTSO-E[3] supports the idea above by stating that the demand side should participate in all markets [4]. To accomplish this, they suggest that market rules should be amended to enable the work of aggregators.

In response to the increased need for flexibility, a large number of concept studies and demonstration activities related to market design changes have been initiated. Some focus on the change of rules in existing, while others introduce new markets.

The ECO-Grid project proposes a new, local real-time market to balance the power system. The market is bid-less and the market operator sets a price every 5 minutes for flexible resources to respond to [5]. The new market fits into the existing market regime between the regulating power market and the frequency-controlled reserves, and opens for smaller units to participate. A neighborhood market is proposed in the Nobel-project [6] aiming at trading locally produced renewable generation. The market model is based on a stock exchange model with continuous trading for 15 minutes' time slots. The iPower project introduces a clearinghouse for flexibility services to facilitate ancillary services at the DSO level ([7], [8]) to avoid local congestion. They distinguish between service types for reservation and scheduling. Activation signals are sent out, and the flexible resources must respond within 15 minutes. The idea of splitting into reservation and scheduling is also supported by Rosen & Madlener [9], who propose a weekly auction for reservation of capacity for every hour of the days in the following week. A local market framework to exploit flexibility from end users is also proposed by Torbaghan et al. [10]. They split between ahead planning including day-ahead and intra-day mechanisms, and real-time dispatching. The DSO is the local market operator, and the energy programs are set such that there will be no congestion issues in the distribution grid. If the market-based planning fails, the DSO will perform real-time dispatching to resolve congestion issues.

The Horizon 2020-project EMPOWER[4] elaborates a local market concept with three basic types of markets: One for local electricity, one for local flexibility and one for other services [11]. The local flexibility market provides flexibility services for local congestion and voltage control. The Smart Energy Service Provider, SESP, acts as a flexibility aggregator with long term contracts with the

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[3] European network of transmission system operators for electricity, www.entsoe.eu

[4] Local Electricity Retail Markets For Prosumer Smart Grid Power Services, www.empowerh2020.eu

flexible consumers and prosumers on one side, and the DSO on the other. The market has the time granularity of 15 minutes [12].

A review of markets for demand side flexibility is given by Eid et al. [13]. They divide the different markets into ancillary services, system balancing and network congestion management, spot markets and generation capacity markets.

Another review is given by Hu et al. [14], who focus on barriers to integrate variable renewable electricity into the wholesale electricity market. They claim that an overhaul is needed for the current EU electricity market design and suggest higher time resolution of trading products, later gate closure times and capacity-based schemes.

Although some of the references above focus on the local and other on the wholesale side of the market, there are some common features: Reservation of flexibility capacity for later use, activation of flexibility near real-time and an energy market for the day-ahead or shorter. Based on these ideas, in this article we define a generalized market design which we believe is representative for a future market design both at the wholesale and the local levels. The design includes the following markets:

- An options market (OM), where flexibility capacity is reserved for potential later use. The trading horizon is several days.
- A spot market (SM), where electricity is traded for the day-ahead or shorter with a time granularity of one hour or less.
- A flexibility market (FM), where flexibility is activated in real-time or close to real-time.

Note that this market framework is partly similar to already existing electricity markets at the wholesale level. One example is the Norwegian market regime, where Statnett's[5] Tertiary reserves options market ("RKOM uke"), Nord Pool's[6] Elspot day-ahead market and Statnett's Tertiary reserves market ("RK"), correspond to the OM, SM and FM, respectively.

A fundamental challenge for market participants in multiple markets, is how to optimally allocate volumes to the different markets. Bidding decisions for multiple, sequential electricity markets have been studied in a small number of papers, all seen from the perspective of a power producer. A literature review regarding this topic is given in [15]. It concludes that the optimal bidding strategy is found when all subsequent markets are taken into account when bids into the first market are decided. First, they review the bidding models, all covering a day-ahead market in different combinations with intraday, balancing and ancillary services markets ([16]–[20]). *Coordinated bidding* is the term they use when taking subsequent markets into account, while the contrary is denoted *separate bidding*. Just a few studies quantify the gain from coordinated bidding. Although these figures are not very high (0,1 to 2%), the gain is expected to increase with increasing price differences between the markets [16].

The problem under consideration in this paper has many similarities with the multi-market bidding studies referenced above. We also use the concept of coordinated bidding. However, our focal entity is not a power producer, but a demand side flexibility aggregator. To our knowledge this has not

[5] Statnett is the Norwegian transmission system operator, see www.statnett.no/en
[6] www.nordpoolspot.com

been covered before. Contrary to the studies above, we also include the OM, where capacity is reserved for later use in FM.

Our starting point is the previous work [21], where we developed a bidding and scheduling model for day-ahead market participation for an energy aggregator. The main objective for the aggregator was to minimize expected costs for supplying electricity to a set of prosumers, while dispatching flexible energy units. The model was formulated as a two-stage stochastic mixed integer program, where the uncertain parameters were represented in scenarios. In the current paper there are three major extensions. We now focus on flexibility (up- and down-regulation) explicitly. Instead of trading in one, single market, now we cover trading in three different markets. The problem is extended from a two-stage to a multi-stage problem.

The contribution from this article is four-fold:

- We develop a mixed integer multi-stage stochastic programming model for coordinated bidding to determine optimal bidding strategies for a flexibility aggregator participating in three sequential markets, including a market for reservation of capacity
- We model explicitly the information revelation process, and take into account that prices may realize differently from the scenarios
- To ensure technically feasible solutions, we put effort into modelling the flexibility units properly to capture physical and economic constraints in the underlying, physical systems
- We perform a realistic case-study based on 4 industrial companies and one aggregator including a quantification and discussion of the value of flexibility and the value of aggregation

The remainder of the paper is organized as follows: Chapter 2 outlines the problem, including descriptions of the trading process and the information structure. The mathematical formulations are presented in Chapter 3, while Chapter 4 contains the case study.

2. Problem description

Flexibility and market design

Let a flexibility aggregator manage a portfolio of flexibility units on behalf of a set of flexibility vendors. The flexibility aggregator's objective is to maximize the profit from the portfolio by trading in a set of markets. Each flexibility vendor has at least one flexibility unit, which can provide services for up-regulation or down-regulation. Up-regulation means increased generation or reduced load, while down-regulation is the opposite. This definition is in line with existing terminology used in balancing markets ([22], [23]). A flexibility unit represents an appliance or a group of appliances that can alter the electricity produced or consumed. In other words, a flexibility unit can represent controllable loads, generators and storages. Although we in this paper focus only on flexibility, we follow the same principles as in our previous work [21] and split flexibility units into discrete units (that can only be switched on or off), continuous units (that can be regulated up or down continuously) and shiftable units (that can be regulated in both directions, but where a net volume constraint must be fulfilled within a set of periods). In addition, we define parameters for maximum and minimum duration of a regulation and minimum rest-time between two regulations. Each flexibility unit has a capability for regulating up or down in each time period.

Up-regulation means selling to the market, and this action comes to an added cost for the flexibility vendor. For a generator, up-regulation cost can be related to extra use of fuel. The cost for reducing load may be related to added cost of alternative solutions, reduced volume of produced goods or loss of comfort. Up-regulation is profitable for the flexibility vendor if the revenue from selling to the market exceeds the cost for performing the up-regulation activity.

For down-regulation it is a bit different. Reduced generation or increased load means buying from the market. This action comes to a reduced cost, for example reduced use of fuel or increased volume of produced goods. Hence, down-regulation is profitable if the added cost from buying in the market is smaller than the reduced cost from performing the down-regulation. In many cases the reduced cost is 0, and down-regulation is profitable only if the market prices are negative.

The aggregator's task is to maximize the value of the flexibility portfolio by trading in three sequential markets as illustrated in Figure 1. In this paper we take the perspective of one market participant, the flexibility aggregator, but there are of course many other entities participating in the same markets. Notice that although the SM is an energy market, the flexibility aggregator participates only with up- and down-regulation.

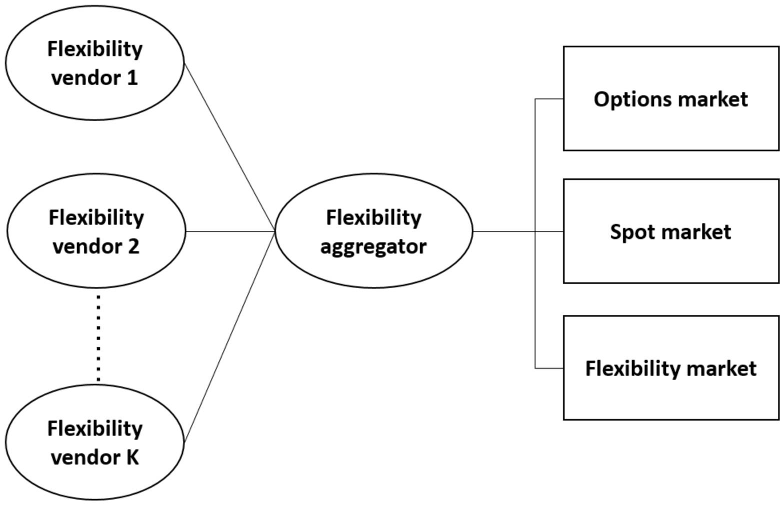

Figure 1. Flexibility vendors, aggregator and markets

The flexibility aggregator can get revenues for flexibility from all the three markets. However, physical activation of the flexibility will be done only for commitments in the SM and FM. Commitments in the OM only means that the volume must be bid to the FM at a later stage and will only turn into a physical obligation if it gets committed in the FM. Notice also, that volumes can be bid to the FM without having been reserved in the OM.

For the ease of exposition, we use one week as the trading horizon for the OM, one day for the SM and the FM and one hour as the time granularity in all markets. In this article we assume step-wise bid-formats for the OM and the FM, while the SM has piece-wise linear bidding curves (see for instance [16]). Further, we assume that all markets are settled according to pay-as-clear principle, also denoted uniform price, as opposed to pay-as-bid [24]. However, other bid formats and settlement principles will not change the basic approach.

The trading process and decision making under uncertainty

The trading process will be sequential: First, the aggregator submits a bid to the OM for one week. The market operator clears the market and publishes the OM prices and commitments. Secondly, the aggregator submits a bid to the SM for the first day in the week. The market operator clears the market and publishes the SM prices and commitments. Thirdly, the aggregator submits a bid to the FM for the first hour. The market operator calls for activations and publishes the FM price. Figure 2 illustrates this trading process. Finally, when the FM is cleared, the flexibility aggregator needs to decide the optimal schedules for each flexibility unit, where the market commitments must be met.

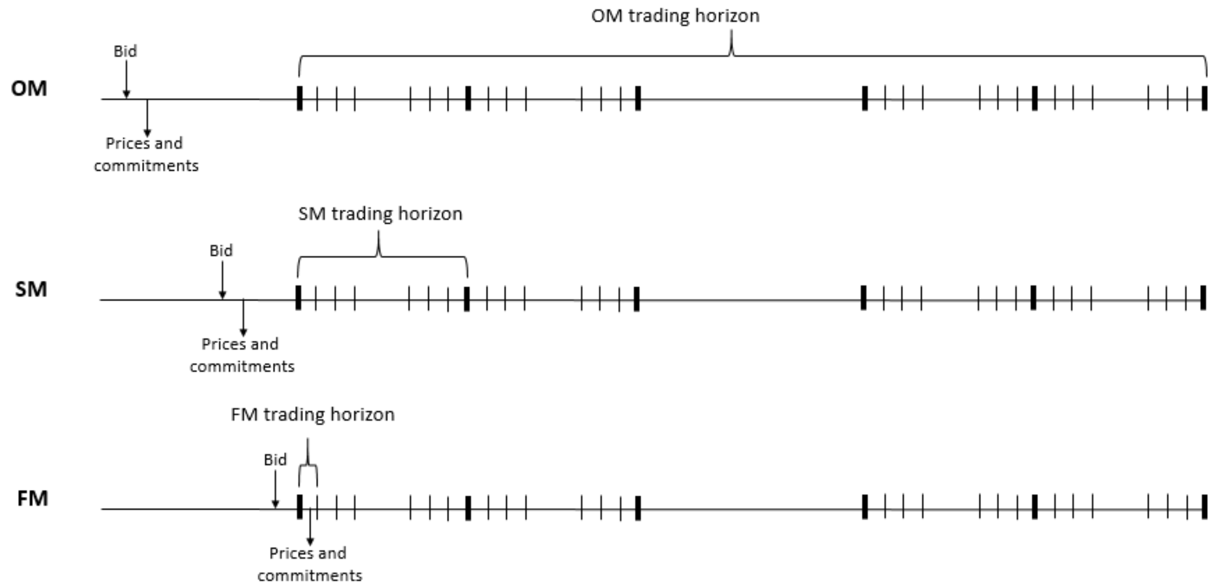

Figure 2. Illustration of the bidding and market clearing process

Next, the process for the FM continues to the next hour, repeatedly until the last hour for that day. Then the SM trade moves to the next day, the FM trade starts for the first hour, then the second hour and so forth. When the FM is finished for the last hour in the week, the OM is cleared for the consecutive week.

The flexibility aggregator's problem is to decide the bids to each of the markets so that the expected profit is maximized. Since the prices are revealed gradually, these decisions must be made under uncertainty. We generate a set of price scenarios for each market, where a scenario represents a possible realization of the prices, with a corresponding probability to occur. Some examples of price scenarios are shown in Figure 16 and 17.

As illustrated in Figure 2 the aggregator receives new price information 176 times a week (one for the OM, 7 for the SM and 168 for the FM), and consequently makes 344 decisions (one OM bid, 7 SM bids, 168 FM bids and 168 schedules). According to stochastic programming theory ([25]–[27]), we might model the process as a 176 stages' scenario tree, where a decision is made in each stage and new information is revealed between two stages. This problem will be mathematically difficult to handle. To make the problem tractable, we choose the following approach:

- We re-establish a new model each time new price information is revealed and a new decision must be made. This approach also makes it possible to capture situations where the prices are realized differently from the pre-generated price scenarios.
- We reduce the number of stages by collapsing down to maximum 3. Number of stages will differ from problem to problem, see below.
- We assume that price information from the FM is published simultaneously for all hours for each day.

In sum, this approach reduces the number of decisions to be made from 344 to 22 (1 OM bid, 7 SM bids, 7 FM bids, 7 scheduling decisions). Below, we explain how the models for the different markets are set up.

The objective for the OM problem is to maximize the expected profit for the whole OM trading horizon (one week). The first stage decision is the OM bid. The optimal bid volume to the OM depends on the balance between expected profits from the OM and the FM on one side and from the SM on the other side. This applies since the volume committed to the OM is reserved for the FM, and can not be bid to the SM. To take into consideration the implications to the OM bid from later decisions, we establish a 3-stage scenario tree, where the SM and FM bid decisions are taken in the second stage and the schedules in the third, see the left hand side of Figure 3. The aggregator then submits the OM bids and receives the realized OM prices and corresponding OM commitments. We have now collapsed the SM and FM decisions into one common stage covering SM decisions for all 7 days and FM decisions for all 168 hours. This is of course a large simplification. However, recall that we implement the first-stage decision (OM bids) and that the later stages are included only to capture their impact to the OM bid decisions. This issue is further elaborated in the Discussion subsection under the Case study.

Next, we move to the SM problem and establish a new three-stage scenario tree. The objective for the SM problem is to decide a SM bid that maximizes the expected profit for the SM trading horizon (one day). The optimal decision depends on the balance between expected profits from the SM and the FM markets, constrained by the OM commitment and the flexibility units. The first stage decision is now the SM bid for the next day. The second stage captures the FM bids, while the third stage covers the schedule decisions for the next day. The aggregator submits the SM bids and receives the realized SM prices and corresponding commitments. The middle part of Figure 3 illustrates the scenario tree.

Then we establish the FM problem. The objective for the FM problem is to decide FM bids that maximize expected profit, taken into account commitments from the OM and SM markets and the flexibility unit constraints. In the first stage, the FM bid decisions are made, while the scheduling decisions are made in the second stage, see the right-hand side of Figure 3. Notice that the FM problem is handled in a two-stage scenario tree. The aggregator submits the FM bids and receives the realized FM prices and corresponding commitments.

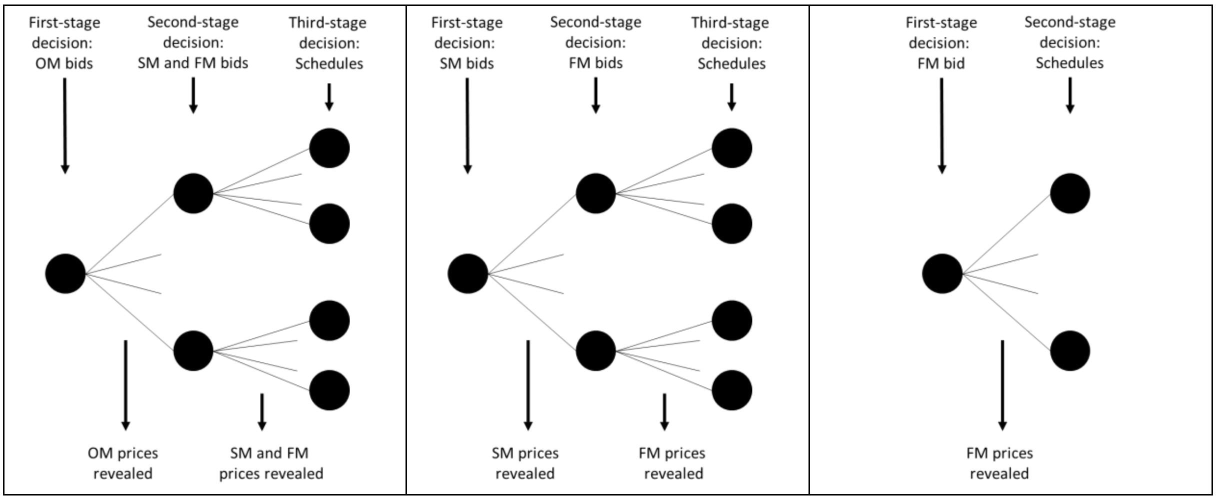

Figure 3. Scenario trees for the OM (left), SM (middle) and FM (right) problems

Finally, the aggregator decides schedules for each flexibility unit. Since all prices and commitments are known with certainty, this problem is deterministic.

3. Mathematical formulation

In this section we outline the mathematical formulation for the bidding and scheduling problems, with one section for each problem type. We describe the sets, parameters and variables successively as they appear. A full list is found in Appendix A. We assume that the aggregator is risk neutral and a price taker.

The OM problem

Objective function

The objective in the OM problem is to maximize the expected total profit over the OM planning horizon $t \in T^1$, where superscript *1* denotes the OM market:

$$\max z^1 = \sum_{s\in S} R_s \left[\sum_{t\in T^1} \begin{Bmatrix} P_{1,t,s}^{up}\gamma_{1,t,s}^{up} + P_{1,t,s}^{down}\gamma_{1,t,s}^{down} + P_{2,t,s}(\gamma_{2,t,s}^{up} - \gamma_{2,t,s}^{down}) \\ +P_{3,t,s}(\gamma_{3,t,s}^{up} - \gamma_{3,t,s}^{down}) - \kappa_{t,s}^{up} + \kappa_{t,s}^{down} \end{Bmatrix} \right]. \tag{1}$$

R_s is the probability for scenario *s*. The first term $P_{1,t,s}^{up}\gamma_{1,t,s}^{up}$ represents the revenues from reservation of up-regulation in the OM market calculated by multiplying the price for reservation $P_{1,t,s}$ in period *t* in scenario *s* with the corresponding commitment $\gamma_{1,t,s}^{up}$. Similarly, $P_{1,t,s}^{down}\gamma_{1,t,s}^{down}$ is the revenue from reserving down-regulation volumes. We assume separate prices for reservation of up- and down-regulation, since volumes can be reserved for both directions in the same period. The second and third terms represent revenues and cost from the SM (market 2) and FM (market 3), respectively. Similar to the OM revenue, $P_{2,t,s}\gamma_{2,t,s}^{up}$ represents the revenue from up-regulation in the SM, while $-P_{2,t,s}\gamma_{2,t,s}^{down}$ represents the cost for down-regulation. The same applies for the FM.

For each regulation unit we calculate the up-regulation added cost as the product of unit regulation added cost P_u^{up} for regulation unit *u* and volume regulated up $\varphi_{u,t,s}^{up}$ in period *t* and scenario *s*. The total aggregated up-regulation added cost $\kappa_{t,s}^{up}$ in period *t* and scenario *s* is the sum of up-regulations over all units *u* and all flexibility vendors *k*.

$$\kappa_{t,s}^{up} = \sum_{k\in K}\sum_{u\in U(k)} P_u^{up}\varphi_{u,t,s}^{up}, \quad t\in T^1, s\in S. \tag{2}$$

Likewise, when we regulate down, we calculate the total aggregated reduced costs $\kappa_{t,s}^{down}$ as the sum of down-regulation reduced cost over all units *u* and all flexibility vendors *k*.

$$\kappa_{t,s}^{down} = \sum_{k\in K}\sum_{u\in U(k)} P_u^{down}\chi_{u,t,s}^{down}, \quad t\in T^1, s\in S. \tag{3}$$

Bid constraints

The OM bid format is step-wise, and the bid constraint is formulated as:

$$\gamma_{1,t,s}^{up} = \chi_{1,i,t}^{up}, \quad P_{1,i} < P_{1,t,s} \le P_{1,i+1}, \; i\in I^1, t\in T^1, s\in S, \tag{4}$$

where $\chi_{1,i,t}^{up}$ is bid volume at bid point i. According to the bidding rules, the volume points must be non-decreasing with increasing price:

$$\chi_{1,i,t}^{up} \geq \chi_{1,i-1,t}^{up}, \quad i \in I^m, i \neq 1, \ t \in T^1. \tag{5}$$

Market commitment constraints

Scheduled regulations $\varphi_{u,t,s}^{up}$ summed over all regulation units *u* and flexibility vendors *k* must equal committed volumes to the SM and the FM in each period *t* and scenario *s*:

$$\sum_{k \in K} \sum_{u \in U} \varphi_{u,t,s}^{up} = \gamma_{2,t,s}^{up} + \gamma_{3,t,s}^{up}, \quad t \in T^1, s \in S. \tag{6}$$

$$\sum_{k \in K} \sum_{u \in U} \varphi_{u,t,s}^{down} = \gamma_{2,t,s}^{down} + \gamma_{3,t,s}^{down}, \quad t \in T^1, s \in S. \tag{7}$$

Flexibility constraints

All regulation units $u \in U$ will have a maximum regulation capability per period for up $W_{u,t}^{up}$ and down $W_{u,t}^{down}$, respectively. The scheduled regulation at each regulation unit must be equal to or lower than the capability:

$$\varphi_{u,t,s}^{up} \leq W_{u,t}^{up}, \quad u \in U, t \in T^1, s \in S. \tag{8}$$

$$\varphi_{u,t,s}^{down} \leq W_{u,t}^{down}, \quad u \in U, t \in T^1, s \in S. \tag{9}$$

Non-anticipativity constraints

We have used a variable splitting formulation where a copy of each of the first- and second- stage variables exist for each scenario. Non-anticipativity constraints [25] are then needed to ensure that the first-stage variables take the same values in all scenarios. Further, the second-stage variables that belong to the same subset of scenarios must also take the same values. Since the OM bid decision is independent of scenario, the OM bid constraint automatically fulfils non-anticipativity constraint for the first-stage. For the second stage, we use the SM bid constraint to ensure non-anticipativity, see the formulation of the SM bid in the SM problem section below. Now, the second-stage bids must be equal for all scenarios belonging to the same scenario group. See illustration in Figure 15.

The SM problem

Objective function

The objective in the SM problem is to maximize the expected total profit over the SM planning horizon $t \in T^2$, which is one day:

$$\max z^2 = \sum_{s \in S} R_s \left[\sum_{t \in T^2} \left\{ P_{2,t,s}(\gamma_{2,t,s}^{up} - \gamma_{2,t,s}^{down}) + P_{3,t,s}(\gamma_{3,t,s}^{up} - \gamma_{3,t,s}^{down}) - \kappa_{t,s}^{up} + \kappa_{t,s}^{down} \right\} \right]. \tag{10}$$

This function is similar to the OM problem, except for the OM market formulations, since the OM market now is cleared and OM prices and commitments are known.

Bid constraints

The bid format for the SM is piece-wise linear, formulated as:

$$\gamma_{2,t,s}^{up} = \frac{P_{2,t,s} - P_{2,i-1}^{bid}}{P_{2,i}^{bid} - P_{2,i-1}^{bid}} \chi_{2,i,t}^{up} + \frac{P_{2,i}^{bid} - P_{2,t,s}}{P_{2,i}^{bid} - P_{2,i-1}^{bid}} \chi_{2,i-1,t}^{up}, \quad P_{2,i-1}^{bid} < P_{2,t,s} \le P_{2,i}^{bid},\ i \in I^2,\ i \ne 1,\ t \in T^2, s \in S. \tag{11}$$

Here, $\gamma_{2,t,s}^{up}$ is the SM commitment in period *t* and scenario *s*, $P_{2,t,s}$ is the SM price in period *t* and scenario *s*, $P_{2,i}^{bid}$ is the bid price for bid point *i* and $\chi_{2,i,t}^{up}$ is the SM bid volume for bid point *i* in period *t*. The same formulation is valid for down-regulation.

According to the bidding rules, the volume points for up-regulation must be non-decreasing with increasing price, and non-increasing for down-regulation:

$$\chi_{2,i,t}^{up} \ge \chi_{2,i-1,t}^{up}, \quad i \in I^2, i \ne 1,\ t \in T^2. \tag{12}$$

$$\chi_{2,i,t}^{down} \le \chi_{2,i-1,t}^{down}, \quad i \in I^2, i \ne 1, t \in T^2. \tag{13}$$

The SM bid volumes $\chi_{2,i,t}^{up}$ for the highest bid point $i = I$ must be smaller than or equal to total available regulation capability $W_{u,t}^{up}$ summed over all regulation units *u* minus committed volume to OM $\gamma_{1,t}^{up}$:

$$\chi_{2,I,t}^{up} \le \sum_{u \in U} W_{u,t}^{up} - \gamma_{1,t}^{up},\ t \in T^2, s \in S. \tag{14}$$

The same formulations are valid for down-regulation.

Market commitment constraints

The SM problem will have market commitment constraints similar to the OM problem.

Flexibility unit constraints

The flexibility unit constraints under the OM problem are also valid in the SM problem. In addition, we now include the time limitations by introducing binary variables. First, $\delta_{u,t,s}^{up-start}$ gets the value 1 in periods where regulation is started up in the beginning of the period. Next, $\delta_{u,t,s}^{up-end}$ gets the value 1 in periods where regulation is stopped at the end of the period. Finally, $\delta_{u,t,s}^{up-run}$ gets the value 1 in periods where regulation is ongoing, but not started or stopped in the same period. We distinguish between up- and down-regulations, so we get six different binary variable types for each regulation unit *u*, period *t* and scenario *s*: $\delta_{u,t,s}^{up-start}, \delta_{u,t,s}^{up-run}, \delta_{u,t,s}^{up-end}, \delta_{u,t,s}^{down-start}, \delta_{u,t,s}^{down-run}, \delta_{u,t,s}^{down-end}$. In the following, we present the constraints for up-regulation, but there will be identical constraints for down-regulation.

The duration of a regulation must be limited to maximum D_u^{up-max} periods:

$$\sum_{j=t}^{t+D_u^{up\text{-}max}-1} \delta_{u,j,s}^{up-end} \ge \delta_{u,t,s}^{up-start}, \qquad u \in U(k), t \in T^2, s \in S, \tag{15}$$

where j is a counter.

Likewise, we limit the duration to minimum D_u^{up-min} periods:

$$\delta_{u,t,s}^{up-start} + \sum_{i=t}^{t+D_u^{up-min}-2} \delta_{u,i,s}^{up-end} \leq 1, \quad u \in U(k), t \in T^2, s \in S. \tag{16}$$

A minimum rest time R_u^{up-min} must exist between two regulations:

$$\delta_{u,t}^{up-end} + \sum_{i=t}^{t+R_u^{up-min}} \delta_{u,i}^{up-start} \leq 1, \qquad u \in U(k), t \in T. \tag{17}$$

The number of regulations must be constrained by the maximum allowable number of regulations B_u^{up-max} for the planning horizon:

$$\sum_{t \in T} \delta_{u,t,s}^{up-start} \leq B_u^{up-max}, \quad u \in U(k), s \in S. \tag{18}$$

The regulated volume $\chi_{u,t,s}^{up}$ can only have a non-zero value in periods where reduction starts, is running or ends. For continuous units the regulated volume must be smaller than or equal to the available regulation volume $W_{u,t,s}$:

$$\varphi_{u,t,s}^{up} \leq \delta_{u,t,s}^{up-active} W_{u,t}^{up}, \qquad u \in U^{cont}(k), \ t \in T^2, s \in S, \tag{19}$$

where $\delta_{u,t,s}^{up-active} = \min((\delta_{u,t,s}^{up-start} + \delta_{u,t,s}^{up-run} + \delta_{u,t,s}^{up-end}),1)$.

For discrete units the regulated volume must be either 0 or equal to the available regulation volume:

$$\varphi_{u,t,s}^{up} = W_{u,t}^{up} \delta_{u,t,s}^{up-active}, \qquad u \in U^{discrete}(k), t \in T^2, s \in S. \tag{20}$$

For shiftable regulation units $u \in U^{shift}(k)$ we in addition to the constraints above define shift time intervals $g \in G(u)$ with a start period T_g^{start} and an end period T_g^{end}. Within each shift interval, the net sum of regulations must be 0:

$$\sum_{t=T_g^{start}}^{T_g^{end}} \left(\varphi_{u,t,s}^{up} - \varphi_{u,t,s}^{down} \right) = 0, \quad u \in U^{shift}(k), g \in G(u), \ s \in S. \tag{21}$$

Note that we did not include any of the constraints involving binary variables under the OM problem. This is a relaxation of the problem, and we selected to do so in order to reduce the calculation times.

We have not included storage units in our formulations. However, that can be done according to the formulations in [21].

Non-anticipativity constraints

Similar to the OM problem, the non-anticipativity constraint for the first stage in the SM problem is automatically fulfilled through the SM bid decision. The second stage constraint will now be ensured by introducing FM bids, see formulations under the FM problem below.

The FM problem

Objective function

The objective in the FM problem is to maximize the expected total profit over the planning horizon $t \in T^3$, which for the FM case are all hours in one day:

$$\max z^3 = \sum_{s \in S} R_s \left[\sum_{t \in T^3} \left\{ P_{3,t,s} (\gamma_{3,t,s}^{up} - \gamma_{3,t,s}^{down}) - \kappa_{t,s}^{up} + \kappa_{t,s}^{down} \right\} \right]. \tag{22}$$

Bid constraints

Since the FM bid format is step-wise, similar to the OM bid, the bid formulations will be equal. However, the FM commitment $\gamma_{3,t,s}^{up}$ is also conditional on the regulation direction in the market, which can be derived from the difference in prices between the SM and FM. The market is up-regulated in a period if $P_{3,t} > P_{2,t}$, down-regulated if $P_{3,t} < P_{2,t}$ and unregulated if $P_{3,t} = P_{2,t}$. The bid constraint then can be formulated as:

$$\gamma_{3,t,s}^{up} = \begin{cases} \chi_{3,i,t}^{up}, \ i \in I^3, t \in T^3, s \in S \ \ if \ P_{3,i}^{bid-up} < P_{3,t,s} \le P_{3,i+1}^{bid-up} \ and \ P_{2,t,s} < P_{3,t,s} \\ 0, \quad i \in I^3, t \in T^3, s \in S \ \ if \ P_{3,t,s} \le P_{2,t,s} \end{cases} \tag{23}$$

$$\gamma_{3,t,s}^{down} = \begin{cases} \chi_{3,i,t}^{down}, \ i \in I^3, t \in T^3, s \in S \ \ if \ P_{3,i}^{bid-up} < P_{3,t,s} \le P_{3,i+1}^{bid-down} \ and \ P_{2,t,s} > P_{3,t,s} \\ 0, \quad i \in I^3, t \in T^3, s \in S \ \ if \ P_{3,t,s} \le P_{2,t,s} \end{cases} \tag{24}$$

According to the bidding rules, the volume points for up-regulation must be non-decreasing with increasing price, and non-increasing for down-regulation:

$$\chi_{3,i,t}^{up} \ge \chi_{3,i-1,t}^{up}, \quad i \in I^m, i \ne 1, t \in T^3. \tag{25}$$

$$\chi_{3,i,t}^{down} \le \chi_{3,i-1,t}^{down}, \quad i \in I^m, i \ne 1, t \in T^3. \tag{26}$$

Volume bid to the FM for up-regulation $\chi_{3,i,t}^{up}$ for the last bid point $i = I^3$ must be greater than or equal to committed volume in the OM:

$$\chi_{3,I,t}^{up} \ge \gamma_{1,t}^{up}, \qquad t \in T^3. \tag{27}$$

Market commitment constraints

The FM problem will have market commitment constraints similar to the OM and SM problems.

Flexibility unit constraints

The FM problem we will have the same flexibility unit constraints as the SM problem.

Non-anticipativity constraints

Since the FM problem is in only two stages, we only need non-anticipativity constraints for the first stage, which are automatically ensured by the FM bid constraints.

The scheduling problem

The objective in the scheduling problem is to maximize the total profit over the planning horizon $t \in T^4$. Now, all trading decisions are made and all commitments are known. The only decision to make is schedules for all the flexibility units so that the difference between down-regulation reduced cost and up-regulation added cost is minimized.

$$\max z^4 = -\kappa_{t,s}^{up} + \kappa_{t,s}^{down}. \tag{28}$$

Since no bid decisions are to be made, we will have no bid constraints. Further, we do not need any non-anticipativity constraints, since all parameters are known with certainty and the problem is deterministic. However, we need the market commitment and flexibility unit constraints. These will be similar to the formulations under the OM and SM problems, see Eq. (6) and (7) and (15) – (21), respectively, but without the notion of scenarios.

4. Case study

Portfolio description

In close cooperation with Statkraft[7] and four Norwegian industrial companies we perform a case study, where we simulate that Statkraft acts as the flexibility aggregator and the industrial companies are flexibility vendors. The flexibility capabilities including constraints have been worked out in close cooperation with the staff at the industrial facilities. The flexibility portfolio is illustrated in Figure 4.

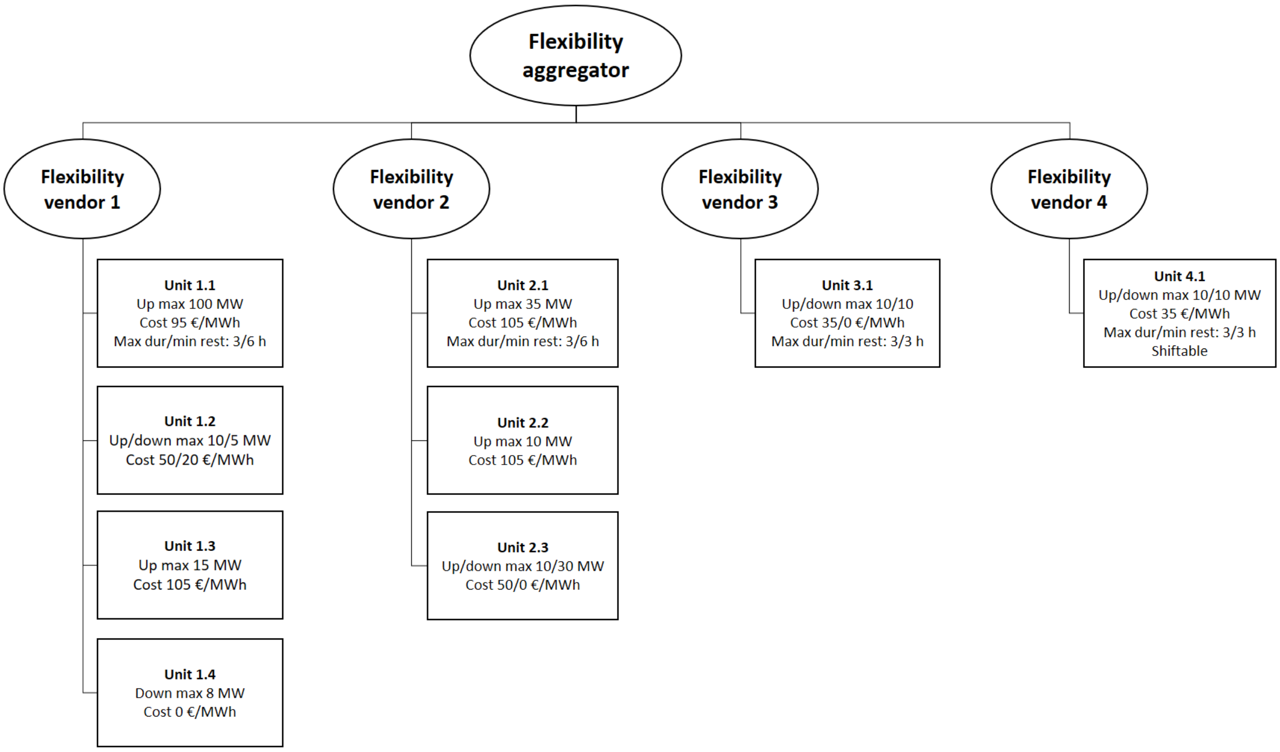

Figure 4. Flexibility portfolio

In total, the portfolio consists of 9 regulation units. Each unit represents a production line or a group of steam generating appliances. Five units can only regulate in one direction (up or down), while four can regulate in both directions. Total capability for up-regulation is maximum 200 MW, while the

[7] www.statkraft.com

corresponding value for down-regulation is 63 MW. Up-regulation costs are 35, 50, 95 and 105 €/MW, while down-regulation reduced costs are 20 and 0 €/MW. Figure 5 shows the aggregated volumes for these costs. Note that the figures show maximum values and do not reflect unavailability or time limitations.

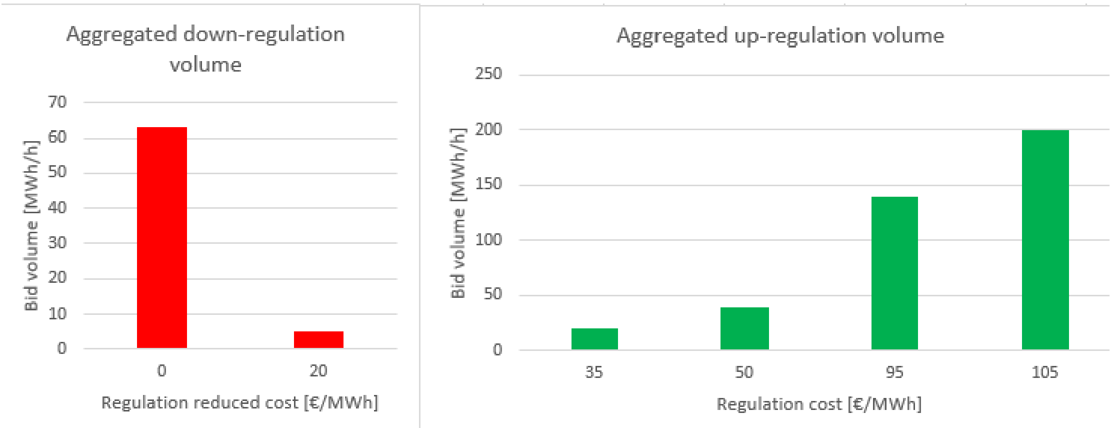

Figure 5. Aggregated volumes for down- and up-regulation

While units 1.2, 1.3, 1.4, 2.2 and 2.3 can perform regulations without any inter-period constraints, units 1.1, 2.1, 3.1 and 4.1 have several constraints: All units have a maximum regulation duration of 3 hours. Further, unit 1.1 and 2.1 have minimum 6 hours' rest time, while unit 3.1 and 4.1 have 3 hours. Finally, unit 4.1 has a volume constraint, where the sum of up-regulation and down-regulation must equal 0 over a day.

Available flexibility for a typical day will be as presented in Figure 4 for each of the hours, except for unit 1.4, which has only 7 MW available for down-regulation from hour 7 to 10, and for unit 2.3, which has possibility to regulate down 30 MW the first half day and up 10 the rest of the day. Moreover, unit 1.1 and 2.1 will be stopped once a month. For these days the capability will be 0 between hour 7 and 18.

Market conditions

To represent the OM, SM and FM, we use prices from Statnett's Tertiary reserves options market ("RKOM uke"), Nord Pool's Elspot day-ahead market and Statnett's Tertiary reserves market ("RK"), respectively. There is one RKOM price per week, and this price is valid for each day from hour 6 to 24. In RKOM resources for up-regulation are reserved for later use in RK. For Elspot and RK there is one price for each hour. The simulations are run on data for the 8 first weeks in 2016, namely from 04.01.2016 to 28.02.2016. Real prices for the three markets are shown in Figure 6 and Figure 7.

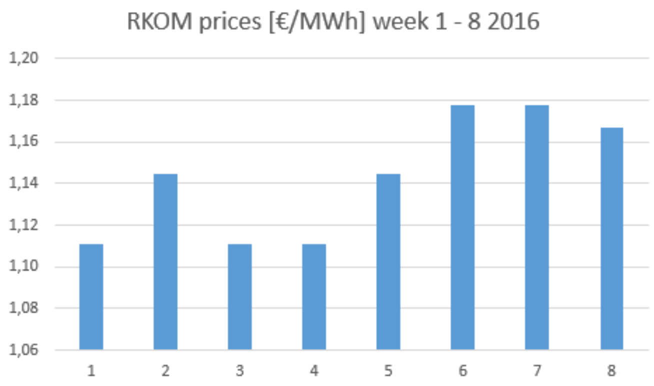

Figure 6. Real RKOM prices for the first 8 weeks of 2016

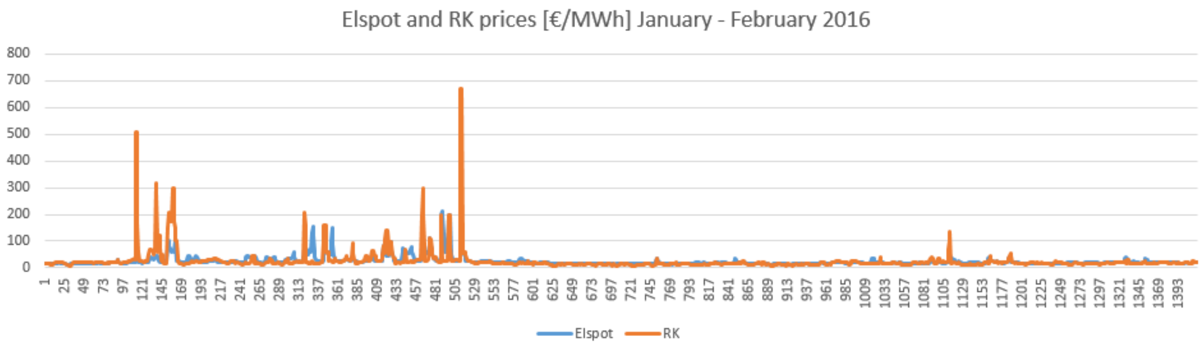

Figure 7. Real Elspot and RK prices for January and February 2016

Note in particular the extraordinarily spiky price pattern for Elspot and RK for January, and the much more dampened situation in February.

Process overview

To perform our analyses, we go through the steps described in Chapter 2, illustrated in Figure 8, where each rectangle with ordinary corners represents a process and a model, while the rectangles with snipped corners represent input or output files.

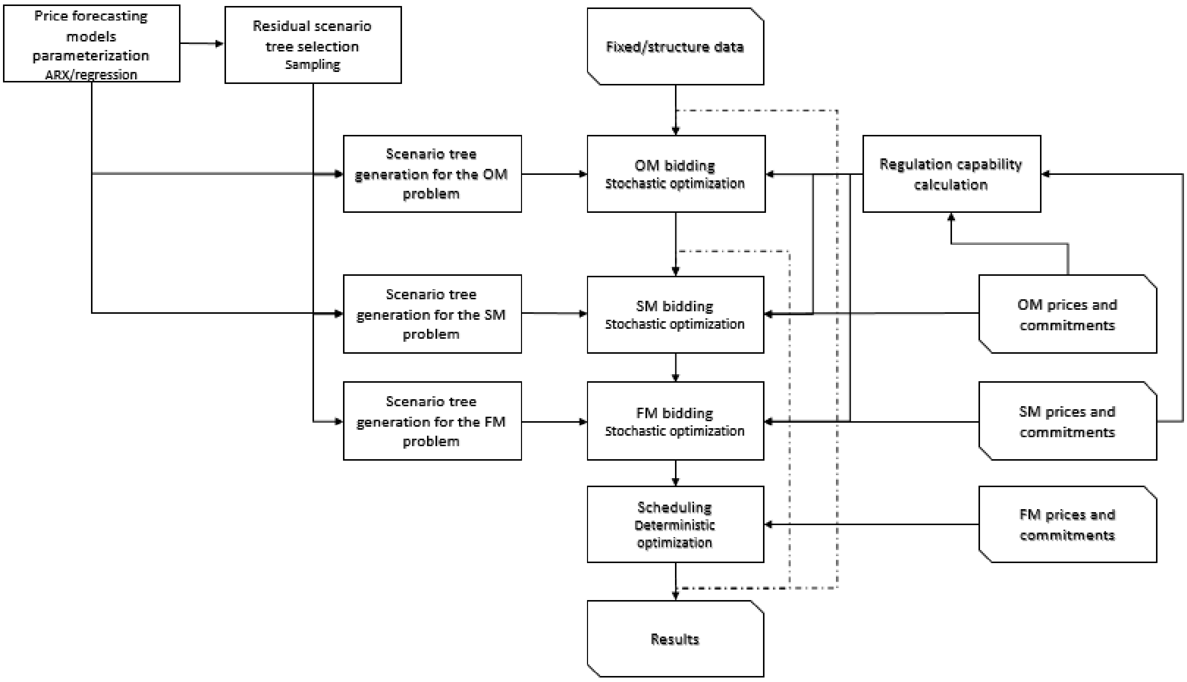

Figure 8. Overview of bidding and scheduling simulation process

The optimization models, as formulated in Chapter 3, are coded in Fico Xpress Mosel, version 3.10.0. Forecasting and scenario generation are handled in MS Excel. Automation of the whole simulation process is implemented in AutoIt.

Results and analysis for one specific day

In this section we analyze one day in detail. We select 15.01.2016, which is Friday in week 2. The OM price for this week cleared at 1.14 €/MWh and is valid for all hours between 6 and 24. An overview of realized prices in SM and FM for the day is shown in Figure 9.

The SM prices vary between 23 and 150 €/MWh with a morning and evening peak. There is up-regulation in FM to high prices (up to 160 €/MWh) from hour 7 to 10, else down-regulation from hour 1 to 3 (to prices below 20 €/MWh) and 14 to 20 (to prices above 20 €/MWh). This means that all up-regulation units are candidates for regulation in the SM and FM, and that unit 1.2 is candidate for down-regulation in the FM. Recall that the prices are not known at the time we make our decisions.

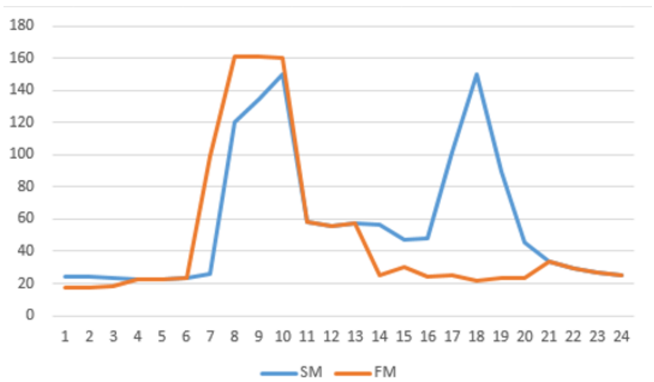

Figure 9. Real prices for the SM and FM for 15.01.2016

Before making decisions for the specific day, we must decide the OM bid for the whole week. Then we need price scenarios for the OM, plus for the SM and FM for all days in the week, which we generate according to the description in Appendix B. The resulting bids are shown in Figure 18. Remember that these bids are valid for hour 6 to 24 all days for week 2, including our focal day, 15.01.2016. Since the OM price for week 2 realized at 1.14 €/MWh, our commitment is 170 MWh/h.

For the SM decision we need price scenarios for the SM and FM, now only for the given day. The resulting SM bids are shown in Figure 19. The bids for the FM problem are presented in Figure 20.

When the FM prices are published, the final schedule to be implemented can be calculated in the scheduling problem. The left part of Figure 10 shows the commitments to each market, the right part shows the net profit, also split down to each revenue and cost element, while Figure 11 shows the schedules for each flexibility unit.

For the hours 6 to 24, the OM commitment is 170 MWh/h, which means that total available volume for SM is 20 MWh/h from 6 – 12 and 30 from 13 – 24. We see that we sell up-regulation in the highest priced hours in SM (8-10 and 17-19) plus some other hours. In FM we first get down-regulation for hours 1 – 3 (where prices are below 20) and then up-regulation for 8 – 10. The optimal utilization of each regulation unit is presented in Figure 11. Note that all constraints are fulfilled: Units 1.1, 2.1, 3.1 and 4.1 run for maximum three hours, unit 1.1 has six hours' rest-time between the regulations, while unit 3.1 has three hours'. Unit 4.1 has 5 MWh down-regulation in hour 1 and 3 and 10 MWh up-regulation in hour 10, which gives net 0.

In total, these decisions give a net profit equal to 45 k€ for the day, where the largest amount of revenues come from FM.

Period	Option up	Spot up	Spot down	Flex up	Flex down
1	0,0	0,0	0,0	0,0	5,0
2	0,0	0,0	0,0	0,0	5,0
3	0,0	0,0	0,0	0,0	5,0
4	0,0	0,0	0,0	0,0	0,0
5	0,0	0,0	0,0	0,0	0,0
6	170,0	0,0	0,0	0,0	0,0
7	170,0	0,0	0,0	0,0	0,0
8	170,0	20,0	0,0	160,0	0,0
9	170,0	20,0	0,0	160,0	0,0
10	170,0	20,0	0,0	160,0	0,0
11	170,0	3,3	0,0	0,0	0,0
12	170,0	10,0	0,0	0,0	0,0
13	170,0	30,0	0,0	0,0	0,0
14	170,0	30,0	0,0	0,0	0,0
15	170,0	0,0	0,0	0,0	0,0
16	170,0	0,0	0,0	0,0	0,0
17	170,0	30,0	0,0	0,0	0,0
18	170,0	30,0	0,0	0,0	0,0
19	170,0	30,0	0,0	0,0	0,0
20	170,0	0,0	0,0	0,0	0,0
21	170,0	0,0	0,0	0,0	0,0
22	170,0	0,0	0,0	0,0	0,0
23	170,0	0,0	0,0	0,0	0,0
24	170,0	0,0	0,0	0,0	0,0
	3230,0	223,3	0,0	480,0	15,0

OM up revenue	3 682	€
SM up revenue	22 510	€
FM up revenue	77 005	€
Regulation up cost	57 963	€
SM down cost	0	€
FM down cost	266	€
Regulation down reduced cost	100	€
Net profit up:	45 234	€
Net profit down:	-166	€
Net profit w/o option	41 385	
Net profit total:	**45 068**	**€**

Figure 10. Market commitments and economic figures for 15.01.2016

	Up-regulation								Down-regulation				
	1.1	1.2	1.3	2.1	2.2	2.3	3.1	4.1	1.2	1.4	2.3	3.1	4.1
1													5.0
2									5.0				
3													5.0
4													
5													
6													
7													
8	100.0	10.0	15.0	35.0	10.0		10.0						
9	100.0	10.0	15.0	35.0	10.0		10.0						
10	100.0	10.0	15.0	35.0	10.0			10.0					
11		3.3											
12		10.0											
13		10.0				10.0	10.0						
14		10.0				10.0	10.0						
15													
16													
17	10.0	10.0				10.0							
18		10.0				10.0	10.0						
19		10.0				10.0	10.0						
20													
21													
22													
23													
24													

Figure 11. Unit schedules for 15.01.2016

Results and analysis for 8 weeks

Figure 12 sums up the results from simulations over 8 weeks. The total net profit is 819 k€, which can be interpreted as the value of flexibility. Note that January contributes with 86 % of the profit, due to the higher price levels in SM and FM compared to February.

	Grand total	Sum January	Sum February
OM up revenue	**168 159**	**70 803**	**97 356**
SM up revenue	**179 695**	**179 044**	**651**
FM up revenue	**945 140**	**916 438**	**28 703**
Regulation up cost	**488 372**	**468 892**	**19 481**
SM down cost	**23 445**	**7 157**	**16 288**
FM down cost	**36 462**	**15 718**	**20 744**
Regulation down reduced cost	**74 194**	**26 554**	**47 640**
Net profit up:	**804 622**	**697 393**	**107 229**
Net profit down:	**14 287**	**3 679**	**10 607**
Net profit w/o option	**636 463**	**626 590**	**9 873**
Net profit total:	**818 908**	**701 072**	**117 836**

Figure 12. Results for 04.01.2016 to 28.02.2016

Profits from down-regulation are almost negligible compared to up-regulation (14 versus 805 k€). One reason is that the portfolio has larger amounts of up-regulation capabilities, another is that most of the down-regulation is profitable only for negative prices. In addition, as we saw in January, the market prices may get extremely high, but rarely extremely negative.

For the up-regulation, 73 % of the revenues stem from FM, while 13 and 14 % stem from OM and SM, respectively. The markets that are specifically designed for flexibility, OM and FM, together contributes with 87 % of the revenues.

For February, OM and SM contributes with 99 % of the up-regulation revenues, but here OM has the largest impact (76 %). In addition, with the low prices in February, net profit for down-regulation is almost three times larger than for January.

To calculate the theoretical upper bound of net total profit and to analyze under what conditions our models are not able to realize the full potential, we repeat the simulations for the 8 weeks' period, but this time we assume that we have perfect information, meaning that we know exactly what the prices will be in the future. Instead of making price scenarios, we enter realized prices as input to our models. This is of course unrealistic in real life, but we perform this in order to analyze the difference between the solutions from the stochastic program (SP) and from calculations with perfect information (PI). The overall results from PI are presented in Figure 13.

	Grand total	Sum January	Sum February
OM up revenue	**190 383**	**93 027**	**97 356**
SM up revenue	**118 893**	**117 791**	**1 102**
FM up revenue	**1 332 090**	**1 288 640**	**43 450**
Regulation up cost	**570 249**	**537 874**	**32 375**
SM down cost	**24 726**	**5 946**	**18 781**
FM down cost	**48 190**	**21 352**	**26 838**
Regulation down reduced cost	**90 600**	**31 700**	**58 900**
Net profit up:	**1 071 118**	**961 585**	**109 533**
Net profit down:	**17 684**	**4 402**	**13 282**
Net profit w/o option	**880 735**	**868 558**	**12 177**
Net profit total:	**1 088 802**	**965 987**	**122 814**

Figure 13. Results for 04.01.2016 to 28.02.2016 based on perfect information

Net total profits are now 1 089 k€ or 33 % higher than results from SP. Most of the difference comes in January.

There are multiple reasons why the solutions differ between SP and PI. First, SP in general chooses strategies that are more robust in meeting different outcomes of the stochastic variables (market prices). In our case this happens for example for the OM decisions, where SP in general decides a lower OM volume. By doing so, the aggregator is more flexible in meeting potential high SM prices. This is in line with stochastic programming theory, see for instance [25].

Further, PI is able to generate larger profits for the volume constrained unit (4.1), since it knows with certainty what all prices are going to be. In SP, this unit is less utilized since we might need to regulate it to high costs to ensure feasible solutions for every scenario.

However, five days contribute with 84 % of the difference in profits between PI and SP. All these are extreme days, with very high prices, in particular in the FM, that are difficult to forecast and to cover in the price scenarios. In Figure 12 and 13 we see that SP allocates more to the SM compared to PI. When the extreme prices occur in the FM, the SP solutions sometimes have allocated volumes to SM and the aggregator can not put maximum volume to the hours with extreme prices in FM. Another reason is that SP in the FM bid has allocated large volumes to FM, but not to the hours where the extreme prices really come. Note that we in our modelling have simplified the FM process, by assuming that bids are sent once a day and that all 24 FM prices are revealed simultaneously. In real life in the tertiary reserves market, this is not the case. The prices are revealed after each hour, and the market participants can change their bids throughout the day. Hence, in a more realistic setting, the problems described above could have been reduced and the profits in SP would have been higher.

This shows that proper price forecasting and scenario generation models are very important. Anyway, no matter how advanced price forecasting models we have, some of the price events in January would be impossible to forecast.

For the scenario generation method, it is particularly important to have a good spread of the scenario fan. Ideally, in the total set of scenarios there should exist one price between each bid price point for each hour. Without this requirement fulfilled, the model sees no probability that the price will realize between these points, and it will be indifferent of what volume to bid here. This might be a problem if the price realizes between these points.

This article focuses on an entity that aggregates flexibility and sells it in markets. Basically, the aggregator performs services on behalf of each flexibility vendor, aiming at lowering the barriers in accessing the market and reducing the transaction costs [1]. However, it is interesting to analyse if the aggregator role has any additional value added impacts on the value chain. To do so, we have performed the simulations for each flexibility vendor separately. The summed results are presented in Figure 14.

Total profits are now 793 k€, which is 26 k€ or 3 % lower than the total profits in the aggregated case (Figure 12). Hence, the value of aggregation is 26 k€. A closer analysis of the results shows that there are different reasons for the added value: First, a larger portfolio of flexibility units provides more robustness to make feasible solutions, and hence, larger volumes can be bid into the markets. An example to illustrate: Assume that unit 2.1 (35 MWh/h) and unit 1.3 (15 MWh/h) are planned out of operation during some hours of the week (but not simultaneously). The total regulating capability will be 50 MWh/h when both run, 35 MWh/h when only 1.2 runs and 15 MWh/h when 1.3 runs. In the disaggregated case none of these units can be bid into OM. In the aggregated case, however, 15 MWh/h can still be bid to OM, since 15 can be provided to hours where both run, 2.1 runs and 1.3 runs. Aggregation releases 15 MWh/h to OM in this example.

Total			
	Grand total	Sum January	Sum February
OM up revenue	157 824	60 468	97 356
SM up revenue	192 146	191 370	776
FM up revenue	944 358	916 997	27 361
Regulation up cost	516 655	497 407	19 248
SM down cost	17 360	5 152	12 208
FM down cost	39 877	17 137	22 740
Regulation down reduced cost	72 071	26 668	45 403
Net profit up:	777 674	671 429	106 245
Net profit down:	14 834	4 379	10 455
Net profit w/o option	619 849	610 960	8 889
Net profit total:	792 508	675 808	116 700
Results from aggregated solutions	818 908	701 072	117 836
Value of aggregation	26 400	25 264	1 136

Figure 14. Results without aggregation

A larger portfolio also gives increased robustness to utilize flexibility units with constraints. Take unit 4.1 as an example. This unit is volume constrained and must, if it has been regulated up at the beginning of the day, be regulated down at the end of the day. If the market is not regulated down, we must regulate up at another unit simultaneously with down-regulation of 4.1. Without aggregation, there are no other candidates to regulate, since vendor 4 only has this unit.

Discussion

The multi-market bidding problem for a flexibility aggregator is a complex task. In order to formulate the problem mathematically and to perform the case study, we have made some simplifications and assumptions.

We assume that the portfolio can be bid aggregated into all markets. Whether this assumption holds, depends on the specific market design and the geographical location for each flexibility vendor. If the flexibility vendors can not be bid aggregated, for instance if they belong to different zones or the FM must be bid down to node level, the value of aggregation will decrease. Further, we have disregarded costs related to grid-tariffs. In cases with dynamic grid prices, for instance with charges related to maximum power feed-in or outtake or to different grid prices in different periods (time-of-use), the grid tariff should also be included in the decision model [28].

We have defined our problem so that the aggregator plans his operations into balance and fulfils the commitments perfectly. In a real-life setting, there will be an imbalance market or some kind of penalization for not meeting obligations. We leave this to future research, but mention that our models managed to find feasible solutions in all cases. Inclusion of the possibility to have imbalances might on one hand introduce additional costs, but on the other hand make it easier to find feasible solutions. We have also assumed that the regulation capabilities are known with certainty, which in a real situation would probably not hold. Further, we have assumed that there is no inter-relation between days regarding regulation capabilities. Then, decisions for the SM and FM can be done for each day separately, without considering later days. In situations where this assumption does not hold, the decision problem will be more complex.

In this paper, we collapse the number of stages down to maximum three and establish a new model for each bid decision to make. This is in contrast to the approach in for instance [16], who solve all problems in one, large multistage program. By applying their approach to our problem, we would for instance in the OM problem have SM prices being realized in seven stages for a week, and where each realization is conditional on realizations in all the earlier stages. Due to our disregard, one could expect a loss in profit, but the analysis with perfect information indicates that this loss is limited. The reason is that different realizations in late stages and their correlations will have little impact to the first stage decision. Further, we also want to pinpoint that making realistic scenarios for late stages is a difficult task. Finally, a strength with our method is that it handles situations where market prices realize differently from the scenarios, which normally will be the case.

The case study is deliberately run for the two first months of 2016, since we then cover both extreme situations with high and volatile prices including many periods with up-regulation and periods with flat and low prices including a lot of down-regulation. To no surprise, we see that the profit potential is largest in situations with high prices and up-regulation. It should be mentioned that January 2016 is peak demand month in the Norwegian electricity market, and hence, the profit figures should be used with care.

The numeric results from the case study indicate that proper models for price forecasting and scenario generation are very important in volatile situations. Implementation of our models in a real life setting would require more advanced forecasting and scenario generation methods which improve how 1) price changes are captured and 2) the scenario fan is spread out. Further, it should be evaluated if the number of price scenarios should be higher. We have seen some days with indifference problems. In addition, stability tests should be performed to ensure that the results are not dependent on the specific scenarios that are generated [29]. However, even with our simplifications and assumptions, we have been able to harvest a large proportion of the potential profit.

We have assumed that the aggregator is risk neutral, with no limitations on the bid volumes. For a real aggregator, we assume that limitations might be put on bid volumes ([17], [30]), for example on the OM bid. Another approach could be to introduce the aggregator’s preferences in the weight of participation in the different markets as outlined in [20]. However, we leave the risk profile topic to later research.

Finally, we have assumed that the aggregator is a price-taker. In particular in local markets, where the number of participants is limited, this assumption might not hold. The aggregator will then become a price-maker, since the selected bidding strategy can influence the market prices. Hence, the prices can not be considered as exogenous. We expect that the value of aggregation in a price-maker context will be even higher than in our study, but we leave to further research to model and analyze such situations.

5. Conclusion and future research

In this paper we propose decision-support models to handle the bidding and scheduling problems for aggregators that manage a portfolio of demand side flexibility by trading in multiple, sequential electricity markets. We have illustrated the application of the models in a case study where we have established a hypothetical portfolio, yet based on real flexibility units. Real data and rules are used from three current Norwegian electricity markets to simulate over a two-month period: January and February 2016. The study shows that our models ensure that bids and schedules are feasible. Further, we have calculated the value of flexibility and analysed how the different markets generate profits and discussed how this is influenced by price levels, price variations and directions of regulation. The total net profit is 819 k€, where 98 % comes from up-regulation and 86 % comes from January, where the prices were very high due to cold temperatures.

To analyze how well the models perform, we have compared with an analysis based on perfect information. We find that the value of the flexibility is 30 % higher with perfect information and that the reason for the loss is two-fold: 1) The stochastic approach chooses strategies that are more flexible to possible different outcomes of the market prices and 2) due to the spiky price situation in January which was very difficult to predict. This also shows the importance of proper price forecasting models and scenario generation methods.

Finally, we have analyzed how the aggregator adds value to the portfolio by comparing to a situation where each flexibility vendor participates in the markets separately. We find that the value is 3 % due to increased ability to commit volumes to the markets and to provide feasible scheduling solutions for the flexibility units.

In our work we disregard imbalances by forcing the schedules to match market commitments and fulfil the flexibility units' constraints perfectly. Further, we assume that available flexibility is known with certainty and do not include potential impact from grid tariffs. Finally, we have simplified the FM by assuming that bid is submitted only once a day with no possibility to change as prices are revealed.

We have only looked at the portfolio as a whole without analysing how the profits should be distributed between the flexibility vendors. In a real-life setting, this will of course be an important question to answer. Furthermore, to analyse the profitability, the investment cost for equipment both at the flexibility vendor side and at the aggregator side, should be quantified.

Acknowledgements

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Appendices

Appendix A. Sets, parameters and variables

M	Set of markets, indexed by *m*, where 1 = options market, 2 = spot market and 3 = flexibility market.
$T^m \subset T$	Subset of time periods where market *m* is valid.
K	Set of flexibility vendors, indexed by *k*.
U	Set of regulation units, indexed by *u*.
$U^{cont} \subset U$	Subset of regulation units of type continuous.
$U^{discrete} \subset U$	Subset of regulation units of type discrete.
$U^{shift} \subset U$	Subset of regulation units of type shiftable.
G	Set of possible load shift time intervals, indexed by *g*.
L	Set of storage units, indexed by *l*.
S	Set of scenarios, indexed by *s*.
I^m	Set of bid points valid for market m, indexed by *i*.

R_s	Probability for scenario *s*.
$P_{1,t,s}^{up}$	Market price for reservation of up-regulation in the OM market in period *t* and scenario *s* [€/MWh].
$P_{1,t,s}^{down}$	Market price for reservation of down-regulation in the OM market in period *t* and scenario *s* [€/MWh].
$P_{m,t,s}$	Market clearing price in market *m* in period *t* and scenario *s* [€/MWh]. These parameters are valid for the SM and FM.
P_u^{up}	Internal cost for regulating up at regulating unit *u* in period *t* and scenario *s* [€/MWh].
P_u^{down}	Internal utility (negative cost) for regulating down at regulating unit *u* in period *t* and scenario *s* [€/MWh].
$W_{u,t}^{up}$	Volume available for regulation up at regulating unit *u* and period *t* [MW].
$W_{u,t}^{down}$	Volume available for regulation down at regulating unit *u* and period *t* [MW].
D_u^{up-max}	Maximum duration of a regulation up at regulating unit *u* [# of periods].
$D_u^{down-max}$	Maximum duration of a regulation down at regulating unit *u* [# of periods].
D_u^{up-min}	Minimum duration of a regulation up at regulating unit *u* [# of periods].
$D_u^{down-min}$	Minimum duration of a regulation down at regulating unit *u* [# of periods].
R_u^{up-min}	Minimum rest time between two regulations up at regulating unit *u* [# of periods].
$R_u^{down-min}$	Minimum rest time between two regulations down at regulating unit *u* [# of periods].
B_u^{up-max}	Maximum number of regulations up at regulating unit *u*.
$B_u^{down-max}$	Maximum number of regulations down at regulating unit *u*.
T_g^{start}	Earliest possible start period for load shift time interval *g*.
T_g^{end}	Latest possible end period for load shift time interval *g*.

$\chi_{m,b,t}^{up}$	Bid volume for up-regulation in market *m* at bid point *b* and period *t* [MW].
$\chi_{m,b,t}^{down}$	Bid volume for down-regulation in market *m* at bid point *b* and period *t* [MW].
$\gamma_{m,t,s}^{up}$	Committed volume for up-regulation in market *m* in period *t* and scenario *s* [MW].
$\gamma_{m,t,s}^{down}$	Committed volume for down-regulation in market *m* in period *t* and scenario *s* [MW].
$\kappa_{t,s}^{up}$	Internal cost for regulating up in period *t* and scenario *s* [€].
$\kappa_{t,s}^{down}$	Internal utility (negative cost) for regulating down in period *t* and scenario *s* [€].
$\varphi_{u,t,s}^{up}$	Power regulated up at regulating unit *u* in period *t* and scenario *s* [MW].
$\varphi_{u,t,s}^{down}$	Power regulated down at regulating unit *u* in period *t* and scenario *s* [MW].
$\chi_{m,b,t}^{up}$	Volume bid for regulation up to market *m* at bid point *b* in period *t* [MW].
$\chi_{m,b,t}^{down}$	Volume bid for regulation down to market *m* at bid point *b* in period *t* [MW].
$\delta_{u,t,s}^{up-start}$	Binary variable = 1 if regulation up starts in the beginning of period *t* for regulating unit *u* in scenario *s*.

$\delta_{u,t,s}^{up-run}$	Binary variable = 1 if regulation up runs for regulating unit *u* in period *t* and scenario *s*.
$\delta_{u,t,s}^{up-end}$	Binary variable = 1 if regulation up ends in the end of period *t* for regulating unit *u* in scenario *s*.
$\delta_{u,t,s}^{down-start}$	Binary variable = 1 if regulation down starts in the beginning of period *t* for regulating unit *u* in scenario *s*.
$\delta_{u,t,s}^{down-run}$	Binary variable = 1 if regulation down runs for regulating unit *u* in period *t* and scenario *s*.
$\delta_{u,t,s}^{down-end}$	Binary variable = 1 if regulation down ends in the end of period *t* for regulating unit *u* in scenario *s*.

Appendix B. Forecasting and scenario generation

Our case study contains three types of uncertain parameters: OM prices, SM prices and FM prices. We make scenario trees for these uncertain parameters, basically following the same approach as in [21]: First, we make a forecasting model and generate price forecast $P_{m,t}^{forecast}$ for the actual market and time periods. Next, we sample residuals $\varepsilon_{m,t}$ and add to the forecast to generate scenarios.

$$P_{m,t,s} = P_{m,t}^{forecast} + \varepsilon_{m,t}, \quad m \in M, t \in T, s \in S. \tag{29}$$

OM price forecasting: We use data from RKOM for 2009 – 2015 to calibrate the model and explain the price for one week by the price one week, two weeks and one year back.

$$p_u^{OM} = \mu + \varphi_1 p_{u-1}^{OM} + \varphi_2 p_{u-2}^{OM} + \varphi_{52} p_{u-52}^{OM} + \varepsilon_u. \tag{30}$$

SM price forecasting: We parameterize the model on data for 2013 to 2015. We need two types of SM price forecasts: one for the OM problem and one for the SM problem. A SM price forecast for the OM problem must be for a whole week (168 prices) and must be based on information available at the time when we make the forecast. We explain the price for an hour by SM price one week back, one year back, the OM price one week back and the temperature forecast. To smooth out extreme values, we model the natural logarithm of the price.

$$\ln p_t^{SM} = \mu + \varphi_1 \ln p_{t-168}^{SM} + \varphi_2 \ln p_{t-8760}^{SM} + \varphi_3 p_{t-168}^{OM} + \varphi_4 \psi_t^{temp} + \varepsilon_t. \tag{31}$$

The SM price forecast for the SM problem will be for 24 hours and is explained by SM price one day, two days and one week back, maximum price one day back, forecasted load published by Nord Pool Spot plus dummy variables for Mondays, Saturdays and Sundays.

$$\begin{aligned} \ln p_t^{SM} = \mu + \varphi_1 \ln p_{t-24}^{SM} + \varphi_2 \ln p_{t-48}^{SM} + \varphi_3 \ln p_{t-168}^{SM} + \\ \varphi_4 \ln mp_t^{SM} + \quad \psi \ln f_t + d_1 D_{Mon} + d_2 D_{Sat} + d_3 D_{Sun} + \varepsilon_t. \end{aligned} \tag{32}$$

For FM prices we have chosen a different approach without making a price forecast. In our case study the FM prices are directly dependent on the SM prices, since the SM price is the starting point for the FM price. In addition, activations in the FM are performed only when incidents occur that are not accounted for in SM, for instance that weather conditions realize differently from the weather forecast or grid components are disconnected due to failures. Such events are difficult to predict due to the randomly characteristics (exogenously driven stochastic process), so we have chosen not to make any price forecasting model for FM.

To generate OM scenarios, we sample residuals from the forecasting model and use property matching (for details, see appendix B in [21]). SM scenarios are also based on residuals sampling from the forecasting models. Due to the strong autocorrelation in the residuals, we sample complete series, 168 values for the OM problem and 24 for the SM problem. However, for the SM and FM price scenarios we have chosen a slightly different method with two objectives: 1) The scenario tree should have values that on expectation are as close as possible to the forecasted value. 2) The scenario tree should span out the scenario fan to limit the indifference problem. The reason behind changing the method is that the first one often do not span out the scenario fan properly. To further reduce the indifference problem, we also add two extreme scenarios related to the lowest and highest realized prices in the calibration period. This is done only to the first stage problem (OM prices for the OM problem, SM prices for the SM problem and FM prices for the FM problem).

FM scenarios are generated the same way as SM scenarios, except that the samples are not based on residuals, but from realized differences between SM and FM prices directly. Note that for the SM problem, FM price scenarios are generated by adding samples to the SM scenario, while for the FM problem, FM scenarios are generated by adding samples to the SM price, which now is known with certainty.

For the OM and SM problem we have a three-stage scenario tree with 34 scenarios. We sample 8 scenarios for the realization of first stage parameters. Next, we sample 32 scenarios for the realization of second stage parameters. The 32 second stage samples are randomly combined with the 8 first stage samples. Finally, we add extreme low and high scenarios for first stage parameters.

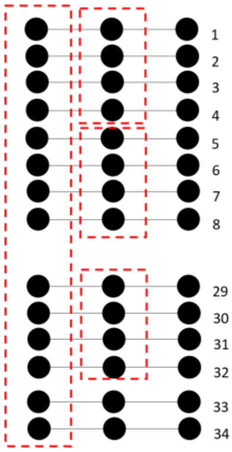

Figure 15. Scenario tree structure for the OM and SM problems

These principles result in scenarios illustrated with some examples in the figures below. Figure 16 shows price scenarios to the OM problem for week 1 (04.01.2016 – 10.01.2016), while Figure 17 shows scenarios to the SM (two first rows) and FM (third row) problems for 04.01.2016.

Figure 16. Examples of scenarios to the OM problem

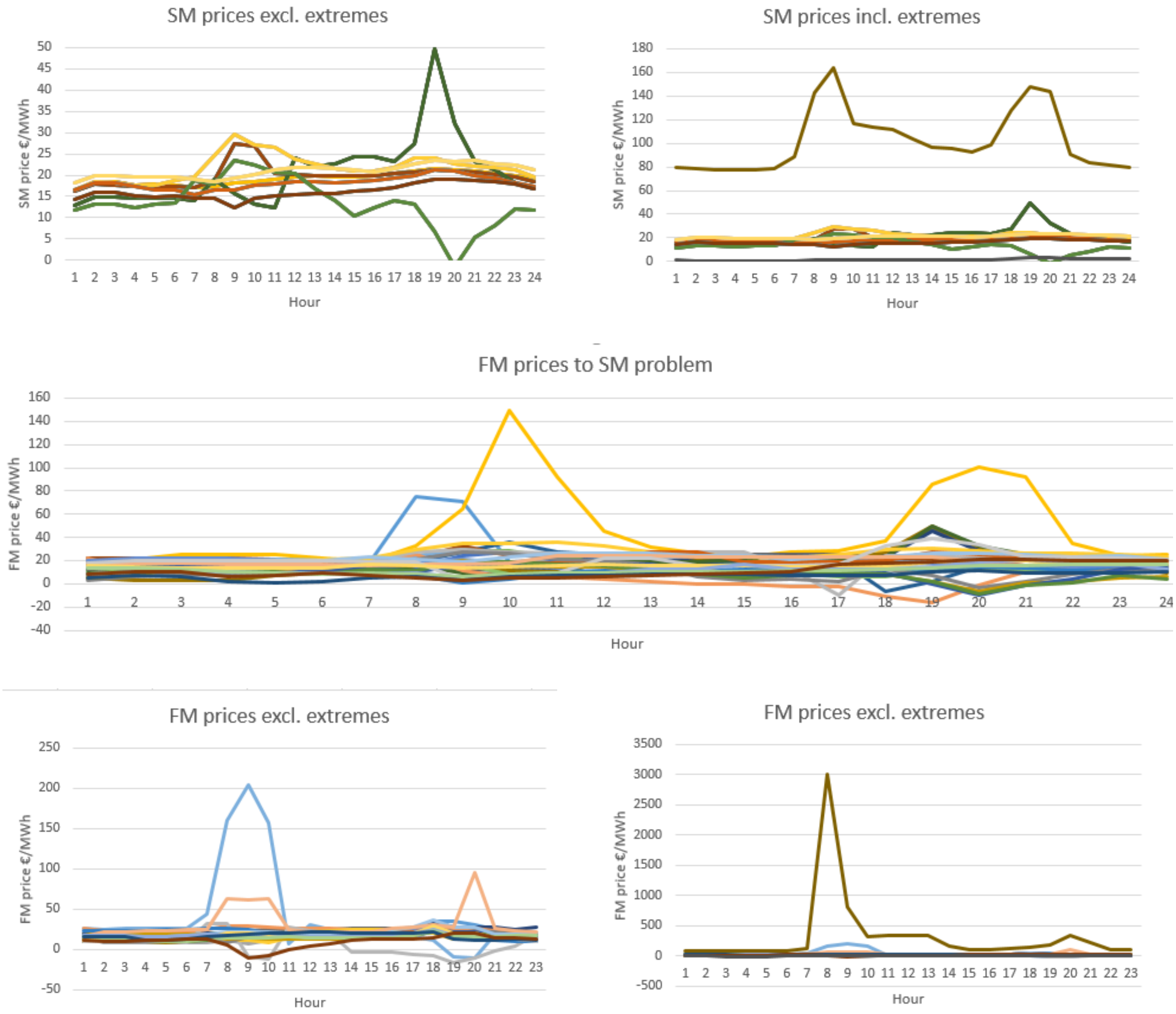

Figure 17. Examples of scenarios to the SM and FM problems

Appendix C. Bid decisions for one day

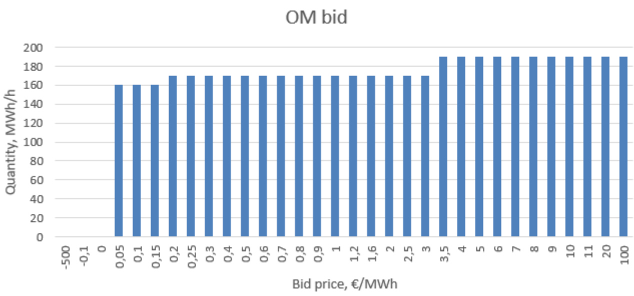

Figure 18. OM bid for week 2 2016

Spot up	-500	-1	0	1	19	20	21	34	35	36	49	50	51	94	95	96	104	105	106	3000
1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	20,0	40,0	140,0	140,0	140,0	190,0	190,0
2	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	20,0	40,0	140,0	140,0	140,0	190,0	190,0
3	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	20,0	40,0	140,0	140,0	140,0	190,0	190,0
4	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	10,0	40,0	140,0	140,0	140,0	190,0	190,0
5	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	10,0	40,0	140,0	140,0	140,0	190,0	190,0
6	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	10,0	20,0	20,0	20,0	20,0	20,0	20,0
7	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0
8	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	10,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0
9	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0
10	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	10,0	20,0	20,0	20,0	20,0	20,0
11	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0
12	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	10,0	20,0	20,0	20,0	20,0	20,0
13	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	10,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0
14	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0
15	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	30,0	30,0	30,0	30,0	30,0	30,0
16	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	20,0	30,0	30,0	30,0	30,0	30,0	30,0
17	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0
18	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0
19	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0
20	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0
21	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0
22	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0
23	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0	30,0
24	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	20,0	30,0	30,0	30,0	30,0	30,0	30,0

Spot d	-500	-1	0	1	19	20	21	34	35	36	49	50	51	94	95	96	104	105	106	3000
1	63,0	63,0	63,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
2	63,0	63,0	20,5	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
3	63,0	63,0	19,2	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
4	63,0	63,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
5	63,0	63,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
6	63,0	63,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
7	62,0	62,0	28,5	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
8	62,0	62,0	62,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
9	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
10	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
11	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
12	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
13	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
14	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
15	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
16	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
17	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
18	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
19	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
20	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
21	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
22	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
23	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
24	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0

Figure 19. SM bids for 15.01.2016

Flex u	-500	-1	0	1	19	20	21	34	35	36	49	50	51	94	95	96	104	105	106	3000
1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	40,0	40,0	40,0	40,0	40,0	40,0	40,0
2	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	40,0	40,0	40,0	40,0	40,0	40,0	40,0
3	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	40,0	40,0	40,0	40,0	40,0	40,0	40,0
4	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	40,0	40,0	40,0	40,0	40,0	40,0	40,0
5	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	40,0	40,0	40,0	40,0	40,0	40,0	40,0
6	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	40,0	40,0	40,0	40,0	40,0	40,0	170,0
7	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	35,0	170,0
8	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	160,0	170,0
9	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	160,0	170,0
10	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	160,0	170,0
11	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	6,7	6,7	6,7	6,7	6,7	6,7	6,7	31,7	170,0
12	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	25,0	170,0
13	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	15,0	170,0
14	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	25,0	170,0
15	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	20,0	20,0	30,0	30,0	30,0	30,0	170,0
16	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0	170,0
17	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	100,0	100,0	115,0	115,0	170,0
18	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	160,0	170,0
19	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	100,0	100,0	100,0	100,0	160,0	170,0
20	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0	90,0	170,0
21	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	45,0	90,0	170,0
22	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	20,0	20,0	170,0
23	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	10,0	10,0	10,0	10,0	10,0	10,0	20,0	20,0	20,0	20,0	170,0
24	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	20,0	20,0	40,0	40,0	40,0	40,0	170,0

Flex dd	-500	-1	0	1	19	20	21	34	35	36	49	50	51	94	95	96	104	105	106	3000
1	43,0	43,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
2	43,0	43,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
3	63,0	63,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
4	63,0	63,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
5	63,0	63,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
6	43,0	43,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
7	42,0	42,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
8	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
9	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
10	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
11	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
12	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
13	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
14	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
15	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
16	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
17	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
18	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
19	5,0	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
20	5,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
21	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
22	15,0	15,0	15,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
23	15,0	15,0	15,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
24	15,0	15,0	15,0	5,0	5,0	5,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0

Figure 20. FM bids for 15.01.2016

Bibliography

[1] Eurelectric, “Flexibility and Aggregation Requirements for their interaction in the market,” Eurelectric, 2014.

[2] GEODE, “Flexibility in Tomorrow’s Energy System - DSOs’ Approach,” GEODE - The voice of local Energy Distributors across Europe, May 2014.

[3] European Commision, “Regulatory Recommendations for the Deployment of Flexibility - EG3 Report Smart Grid Task Force,” European Commission, Jan. 2015.

[4] ENTSO-E, “ENTSO-E Market Design Policy Paper.” ENTSO-E, Sep-2014.

[5] D. Gantenbein, C. Binding, B. Jansen, A. Mishra, and O. Sundström, “EcoGrid EU: An efficient ICT approach for a sustainable power system,” in *Sustainable Internet and ICT for Sustainability (SustainIT), 2012*, 2012, pp. 1–6.

[6] D. Ilic, P. G. Da Silva, S. Karnouskos, and M. Griesemer, “An energy market for trading electricity in smart grid neighbourhoods,” in *2012 6th IEEE International Conference on Digital Ecosystems Technologies (DEST)*, 2012, pp. 1–6.

[7] K. Heussen, D. E. M. Bondy, J. Hu, O. Gehrke, and L. H. Hansen, “A clearinghouse concept for distribution-level flexibility services,” in *IEEE PES ISGT Europe 2013*, 2013, pp. 1–5.

[8] C. Zhang, Y. Ding, N. C. Nordentoft, P. Pinson, and J. Østergaard, “FLECH: A Danish market solution for DSO congestion management through DER flexibility services,” *J. Mod. Power Syst. Clean Energy*, vol. 2, no. 2, pp. 126–133, Jun. 2014.

[9] C. Rosen and R. Madlener, “Regulatory Options for Local Reserve Energy Markets: Implications for Prosumers, Utilities, and Other Stakeholders,” SSRN Paper 2548515, Oct. 2014.

[10] S. S. Torbaghan, N. Blaauwbroek, P. Nguyen, and M. Gibescu, “Local market framework for exploiting flexibility from the end users,” in *2016 13th International Conference on the European Energy Market (EEM)*, 2016, pp. 1–6.

[11] I. Ilieva, B. Bremdal, S. Ø. Ottesen, J. Rajasekharan, and P. Olivella-Rosell, “Design characteristics of a smart grid dominated local market,” presented at the CIRED Workshop, Helsinki, Finland, 2016.

[12] P. Olivella-Rosell, E. Bullich-Massagué, M. Aragüés-Peñalba, A. Sumper, S. Ø. Ottesen, J. Vidal-Clos, R. Villafáfila-Robles, “Optimization problem for meeting distribution system operator requests in local flexibility markets with distributed energy resources,” *Appl. Energy*, vol. 210, no. Supplement C, pp. 881–895, Jan. 2018.

[13] C. Eid, P. Codani, Y. Perez, J. Reneses, and R. Hakvoort, “Managing electric flexibility from Distributed Energy Resources: A review of incentives for market design,” *Renew. Sustain. Energy Rev.*, vol. 64, no. Supplement C, pp. 237–247, Oct. 2016.

[14] J. Hu, R. Harmsen, W. Crijns-Graus, E. Worrell, and M. van den Broek, “Identifying barriers to large-scale integration of variable renewable electricity into the electricity market: A literature review of market design,” *Renew. Sustain. Energy Rev.*, vol. 81, no. Part 2, pp. 2181–2195, Jan. 2018.

[15] G. Klæboe and O. B. Fosso, “Optimal bidding in sequential physical markets #x2014; A literature review and framework discussion,” in *IEEE PowerTech (POWERTECH), 2013 Grenoble*, 2013, pp. 1–6.

[16] T. K. Boomsma, N. Juul, and S.-E. Fleten, “Bidding in sequential electricity markets: The Nordic case,” *Eur. J. Oper. Res.*, vol. 238, no. 3, pp. 797–809, Nov. 2014.

[17] E. Faria and S.-E. Fleten, “Day-ahead market bidding for a Nordic hydropower producer: taking the Elbas market into account,” *Comput. Manag. Sci.*, vol. 8, no. 1–2, pp. 75–101, Sep. 2009.

[18] N. Löhndorf and S. Minner, “Optimal day-ahead trading and storage of renewable energies—an approximate dynamic programming approach,” *Energy Syst.*, vol. 1, no. 1, pp. 61–77, Jan. 2010.

[19] M. A. Plazas, A. J. Conejo, and F. J. Prieto, “Multimarket optimal bidding for a power producer,” *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 2041–2050, Nov. 2005.

[20] C. Triki, P. Beraldi, and G. Gross, “Optimal capacity allocation in multi-auction electricity markets under uncertainty,” *Comput. Oper. Res.*, vol. 32, no. 2, pp. 201–217, Feb. 2005.

[21] S. Ø. Ottesen, A. Tomasgard, and S.-E. Fleten, “Prosumer bidding and scheduling in electricity markets,” *Energy*, vol. 94, pp. 828–843, Jan. 2016.
[22] I. Wangensteen, *Power System Economics: The Nordic Electricity Market*. Tapir Academic Press, 2011.
[23] M. H. J. Bollen, *The Smart Grid: Adapting the Power System to New Challenges*. Morgan & Claypool Publishers, 2011.
[24] S. Oren, “When is a pay-as bid preferable to uniform price in electricity markets,” in *IEEE PES Power Systems Conference and Exposition, 2004.*, 2004, pp. 1618–1620 vol.3.
[25] P. Kall and S. W. Wallace, *Stochastic programming*. Wiley, 1994.
[26] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*. Springer Science & Business Media, 2011.
[27] A. J. Conejo, M. Carrión, and J. M. Morales, *Decision Making Under Uncertainty in Electricity Markets*. Springer Science & Business Media, 2010.
[28] S. Ø. Ottesen and A. Tomasgard, “A stochastic model for scheduling energy flexibility in buildings,” *Energy*, vol. 88, pp. 364–376, Aug. 2015.
[29] M. Kaut and S. W. Wallace, *Evaluation of scenario-generation methods for stochastic programming*. Humboldt-Universität zu Berlin, Mathematisch-Naturwissenschaftliche Fakultät II, Institut für Mathematik, 2003.
[30] S. J. Deng, Y. Shen, and H. Sun, “Optimal Scheduling of Hydro-Electric Power Generation with Simultaneous Participation in Multiple Markets,” in *Power Systems Conference and Exposition, 2006. PSCE ’06. 2006 IEEE PES*, 2006, pp. 1650–1657.