Energy Proceedings
Vol 29, 2022
ISSN 2004-2965

An Optimal Bidding Model to Market Flexibility on the Balancing Electricity Markets[#]

Christoph Gärtner[1*], Elias Röger [1], Till Heller [2]

1 Fraunhofer Institute for Industrial Mathematics ITWM, Department Financial Mathematics, Fraunhofer-Platz 1, 67663 Kaiserslautern, Germany

2 Fraunhofer Institute for Industrial Mathematics ITWM, Department Optimization, Fraunhofer-Platz 1, 67663 Kaiserslautern, Germany

ABSTRACT

In order to stabilize short-term fluctuations in the network frequency, flexibility is offered on balancing electricity markets. With the reformation of the German balancing markets and the opportunity to market secondary balancing energy independently of capacity, short-term flexibilities can now be traded more easily. In this paper, we describe a robust optimization problem for marketing balancing power in these markets. Starting from forecasts on acceptance probabilities and activation durations estimated from historical values, we compute price-quantity pairs that define bids placed on the reserve markets. We present a backtesting study over the period 04/2021 to 11/2021 and, thus, evaluate the potential of flexibility marketing on the secondary control markets.

Keywords: electricity markets, balancing energy, robust optimization, optimal bidding, demand side management, flexibility marketing

NOMENCLATURE

Abbreviations	
aFRR	Automatic Frequency Restoration Reserve
RCM	Reserve capacity market
REM	Reserve energy market
BSP	Balancing Service Provider
TSO	Transmission System Operator
Symbols	
K	Set of 4h reserve energy products +/-
k	Single 4h reserve energy product
N	Number of bids on RCM
M	Number of bids on REM

1. INTRODUCTION

The increasing share of fluctuating renewable energy sources can cause unforeseen short-term imbalances in the system. This requires stabilizing mechanisms that ensure automatic frequency restoration of the system at short notice. The is called electricity balancing. Electricity balancing becomes necessary when the system frequency deviates from normal and is activated in real-time by the transmission system operators (TSO).

In this work we discuss the German secondary balancing electricity market (automatic Frequency Restoration Reserve, aFRR). In Germany, the TSO's are responsible for the procurement of balancing energy in order to maintain standard system frequency. More information on balancing energy, its context in the system and the different market players and roles thereof can be found in [2]. They do this by purchasing balancing energy from pre-qualified balance service providers (BSPs) in an auction-based market. For a new market participant to become a BSP, there exists a pre-qualification process of the TSO that needs to be carried out to verify technical readiness of the concerned power units [10]. Depending on whether the system frequency is below, or above normal, positive, or negative balancing energy is activated. This is called upward- or downward-regulation respectively.

Since mismatches in the system of demand and supply are more likely to happen with a greater amount of volatile producer in the energy mix, the need of balancing the system at adequate costs becomes more relevant than ever. Mismatches can occur because of power plant outages or overproduction of wind parks for example. When this happens the TSO responsible for the affected load-frequency control area will step in to activate the balancing electricity necessary to achieve equilibrium. There exist various kinds of balancing

* Corresponding author at Fraunhofer Institute for Industrial Mathematics ITWM, Department Financial Mathematics, Fraunhofer-Platz 1, 67663 Kaiserslautern, Germany

Email-address: christoph.gaertner@itwm.fraunhofer.de (C. Gärtner)

electricity. These differ in their availability activation time, i.e., how quickly the energy is available to the TSO for activation [8].

This paper is part of the outcome of the research project *FlexEuro* with the overarching theme of cross-market optimization in electricity markets. Our main goal is a cross-market optimization for marketing a virtual battery on three prominent German power markets, i.e., the Day-Ahead market (DA), the Intraday market (ID) and reserve energy markets. For a detailed description of the setting and the virtual battery design, we refer to [6]. Due to different temporalities of the individual markets, different decisions, i.e., bids, have to be made at different points in time. In our case, the result of the first decision is a distribution of flexibility among the considered markets based on profit forecasts for them. Subsequently, further optimizations are done for the individual markets, which have the allocated flexibility as input. Here, we focus on the decisions regarding the reserve energy markets.

Recent works have already dealt with optimal bidding on the German balancing power market. In [7], the authors present a decision-theoretic framework for deriving bidding strategies for suppliers in Germany and Austrian balancing power market. They allow the integration of the suppliers' price expectation when determining optimal bids. The authors evaluate their framework on empirical auction data from January 2014 to May 2016. The auction design in that time frame was based on weekly auctions with two different reserving periods which structurally significantly different from our market situation. Another notable difference is that balancing capacity and energy were traded in a single auction, which was more restrictive than today from the perspective of the supplier. In [5] the balancing power market is also considered as part of the optimization of bids in sequential markets. Similar to our approach they model the acceptance probability of given price levels. The authors use data from between July 2019 and March 2020 which is before the most recent change in market design. Moreover, they only focus on balancing capacity market while excluding balancing energy from their study.

In recent years the German balancing energy markets have been subject to much change, especially in the market and auction design. Due to several external regulatory interventions because of excessive balancing prices for example, the analysis of price data on these markets has been rather difficult since the data is scarce.

The implementation of a secondary balancing energy market has brought new opportunities and challenges to the scenery of electricity trading. Whereas reserve capacity and energy has been traded in the same auction up until now, the auction design has changed in late 2020. Markets participants can now offer reserve capacity and energy separately under some minor offer restrictions [9]. For making writing easier we use the terms balancing energy and reserve energy interchangeably. We write RCM and REM for reserve capacity market and reserve energy market respectively.

In the RCM a bidder gets remunerated, simply for reserving a certain capacity. In contrast, the REM is an energy-only market, i.e., the bidder is only remunerated for the offered capacity that has been activated by the TSO. In this case the bidder gets paid for the delivered energy.

Accepted bids on the capacity market obliges the BSP to offer the same total amount of capacity on the energy market. This serves as a guarantee for the TSOs to be able to cover predicted demand of balancing energy at any time. On the other hand, one is still allowed to get involved in the balancing energy auction even when capacity bids have been rejected by the merit order list. Those bids are called free energy bids. This opens up attractive marketing opportunities for BSPs to trade their short-term flexibility. This new system was designed to stimulate market participation, promote competition, and facilitate market entry for smaller market participants among other reasons.

The current market design of the balancing markets now provides for a split into the capacity and the energy market, on which 4-hour blocks can be traded daily for the corresponding day. This is also possible separately for positive and negative capacity (resp. energy).

The remaining content of the paper is structured as follows: In Section 2 on methodology, we introduce an optimization bidding problem of a potential market participant as well as how we estimate the needed input parameters. In Section 3, we discuss the results of the optimization problem based on the estimated parameter inputs. We then conclude with a short outlook on future regulatory changes in the market planned and the much-discussed PICASSO project as well as future research directions.

2. METHODOLOGY

In this section we give a formulation of the optimization problem for computing bids on the RCM and REM. Furthermore, we describe how to forecast the acceptance probabilities and the activation durations given historical data.

2.1 Optimization Problem Formulation

We consider the Frequency Restoration Reserve with automatic activation (aFRR) in Germany which consists of the reserve capacity and the reserve energy market. Further, we focus on a reserve energy provider to market a given input capacity on the German secondary reserve energy market. We denote the set of products by

$$K = \{\pm 00\_04, \pm 04\_08, \dots, \pm 20\_24\}.$$

Since the only risk consists of opportunity costs, we focus on the expected profit the market participant can make on both markets simultaneously. We model the auction of both markets by regarding different bidding scenarios of our market player. Additionally, we formulate the profit function on both markets as a basis for an optimization problem. We are interested in finding an optimal bidding solution such that the profit is maximized. The solution explicitly shows how to distribute the total given capacity that is available to the provider among the different products on a given day. Therefore, we rely on forecasted acceptance probabilities on the RCM and the activation duration on the REM as input for the optimization problem. For an overview over the bidding sequence on both markets from the perspective of a BSP and the potential balancing energy activation, see Figure 2.

2.1.1 Reserve Capacity Market

In the following, we describe the constraints for the bidding problem regarding the RCM. Note that a similar approach can be found in [11]. There, however, the authors focus on the trading strategies on the primary reserve market which is fundamentally different in market design than our situation.

For a fixed product we consider N *bids* on the RCM. A *bid* on the RCM market is given by $(m_i^{RC}, \mathrm{p_i^{RC}})$, where the decision variable m_i^{RC} is the offered volume [in MW] and the input parameter $\mathrm{p_i^{RC}}$ the price level [in $\frac{€}{\mathrm{MW}}$] for all $i = 1, \dots, N$. We assume the bids to be ordered by increasing price levels, i.e., $p_i^{RC} \leq p_{i+1}^{RC}$ for all $i = 1, \dots, N$. Furthermore, we define by *bidding scenario* i the event that exactly the first i offers are accepted. Corresponding to these bidding scenarios, we denote by q_i^{RC} the probability for scenario i to occur. Define q_0^{RC} as the probability that none of the N *bids* on the RCM are accepted.

Now, given the probabilities, define the *expected profit* f_k^{RC} of product k as

$$\sum_{i=1}^{N} q_i^{RC,k} \left(\sum_{j=1}^{i} m_j^{RC,k} \cdot p_j^{RC} \right),$$

where $\mathrm{m_i^{RC,k}}$ denotes the offered volume at price level $\mathrm{p_i^{RC}}$ for product k. The total available volume for product k is bounded by the given input flexibility $\mathrm{m^{RC}}$ that is available to the energy provider on that day. Thus, the constraints

$$\sum_{i=1}^{N} m_i^{RC,k} \leq m^{RC}$$

are added to our optimization problem for all products $k \in \mathrm{K}$. The *total expected profit of the RCM* is denoted by the variable $\mathrm{f^{RC}}$ and is simply defined as the sum of expected profits from all products in K, i.e.

$$f^{RC} = \sum_{\mathrm{k \in K}} f_k^{RC}.$$

2.1.2 Reserve Energy Market

For the REM we follow a slightly different approach. As before, we denote a bid on the REM by $(m_i^{RE}, \mathrm{p_i^{RE}})$ for all $i = 1, \dots, M$ for given price levels $\mathrm{p_i^{RE}}$ [in $\frac{€}{\mathrm{MWh}}$]. Again, we optimize the volumes m_i^{RE} for each given input price level. In the same way as for the constraints regarding the RCM, the input flexibility is denoted by $\mathrm{m^{RE}}$ and bounds the sum of offered volumes, i.e.

$$\sum_{i=1}^{N} m_i^{RE,k} \leq m^{RE}.$$

Note that by regulations the accepted capacity on the RCM auction needs to be offered on the REM auction. Since we additionally allow free bids on the REM, we do not need to restrict the volume of bids on the REM by the accepted volume on the RCM.

For a fixed day, we define the *reserve energy activation amount* in MW at second t and product k as $\mathrm{S_t^k}$. Furthermore, let $\Psi^{\mathrm{k}}(\mathrm{p})$ be the sum of offered capacity in MW at the REM for product k from all offers with an ask price at most p. This can be viewed as the total capacity amount activated by the TSO before offer with ask price p will be activated. With this, we are able to define the *aFRR activation duration* for a given product k and a price level p as

$$\mathrm{L^k(p)} = \sum_{\mathrm{t \in k}} 1_{\mathrm{S_t^k \geq \Psi^k(p).}} \tag{1}$$

In *Figure 1* the idea for the activation duration and its computation is illustrated in an example. The *expected activation duration* $\alpha^{\mathrm{k}}(\mathrm{p})$ of *aFRR activation* for a given price offer p and a product k is defined as

$$\alpha^{\mathrm{k}}(\mathrm{p}) \coloneqq \mathrm{E}\left[\mathrm{L^k(p)}\right]. \tag{2}$$

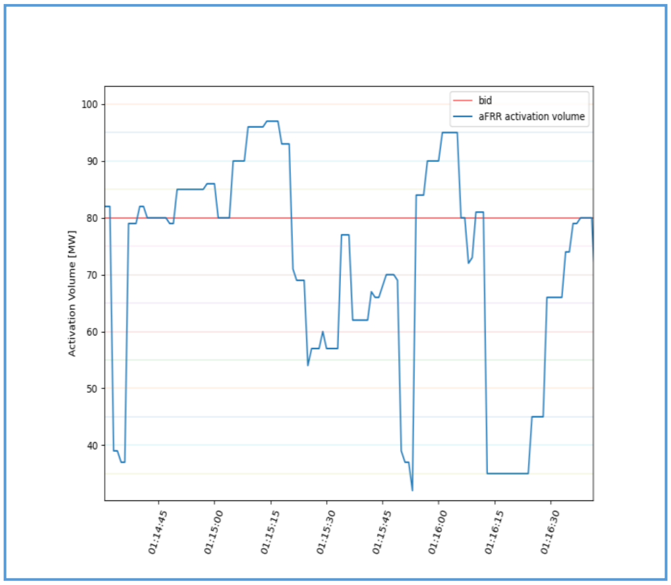

Figure 1: Exemplary aFRR activation duration. The blue line depicts the activated volume in each second, whereas the red line indicates the considered bid. The colored lines in the background correspond to stacked offer pairs given by capacity [MW], energy price [EUR/MWH]. The activation duration can be computed as the sum of time intervals where the activation volume is higher than the line of the considered bid.

We denote the series of expected activation durations for different price levels by (α^k). Now, given an expected activation duration (α^k) and product k, the *expected profit on the aFRR market* f^{RE}_{k,α^k} is defined as

$$\sum_{i=1}^{M} p_i^{RE} \cdot m_i^{RE,k} \cdot \alpha_i^k. \qquad (3)$$

We add constraints for all series of expected activation durations (α^k) of the following form

$$f_k^{RE} \leq f^{RE}_{k,\,\alpha^k}$$

Note that this can be seen as a risk-averse strategy, since we try to maximize the profit over all considered activation duration series and, thus, in particular for the worst-case scenario. The *total expected profit of the REM* is now simply given as the sum of expected profits over all products, i.e.

$$f^{RE} = \sum_{k \in K} f_k^{RE}.$$

2.1.3 Objective Function

In total, we try to maximize the sum over both profits, i.e., the objective function is given as

$$\max\ f^{RC} + f^{RE},$$

where the decision variables are the volumes for given price levels on both RCM and REM. In the next section we describe how the needed input parameters are forecasted.

2.2 Forecasted Input Parameters

The optimization problem above relies on several input parameters. As described above, we consider bidding scenarios for the RCM. For each of the bidding scenarios an acceptance probability is needed that denotes the probability that the corresponding bid is the highest accepted bid. For the REM, the activation durations per given price level are needed. The price levels are chosen accordingly to price forecasts of the day-ahead market. For positive energy we choose price levels on the REM, above the forecasted day-ahead price. For a detailed explanation on the used day-ahead price forecasts, we refer to [12]. The activation durations denote the total time period for which a bid is activated by the TSO. In the following, we describe how we estimated future parameter values depending on historical data.

2.2.1 Estimating the acceptance probabilities for the RCM

We estimate the acceptance probabilities $q_i^{RC,k}$ on the RCM from historical data. To estimate this quantity, we use the time-series of daily marginal prices per product *k* and denote it by $\pi_d^{RC,k}$. In order to get an estimate of the short-term distribution of the marginal prices we restrict ourselves to 30 days before the observation. Every day *d* gets assigned the empirical distribution function

$$\widehat{F_d}(p) = \frac{1}{30} \sum_{j=1}^{30} 1_{\pi_{d-j}^{RC,k} \leq p}$$

The probabilities are computed as

$$\begin{aligned}
q_0^{RL,k} &= \widehat{F_d}(p_1) \\
q_1^{RL,k} &= \widehat{F_d}(p_2) - \widehat{F_d}(p_1) \\
q_2^{RL,k} &= \widehat{F_d}(p_3) - \widehat{F_d}(p_2) \\
&\vdots \\
q_N^{RL,k} &= 1 - \widehat{F_d}(p_N)
\end{aligned}$$

2.2.2 Estimating activation durations for the REM

To calculate the expected activation duration of aFRR as defined in (2), we first compute $L^k(p)$ accordingly to (1) for our given price levels $p_1^{RE}, \ldots, p_M^{RE}$ for every day in the data set, see *Figure 1*. We then compute different activation duration series by computing different summary statistics over past observations of $L^k(p)$.

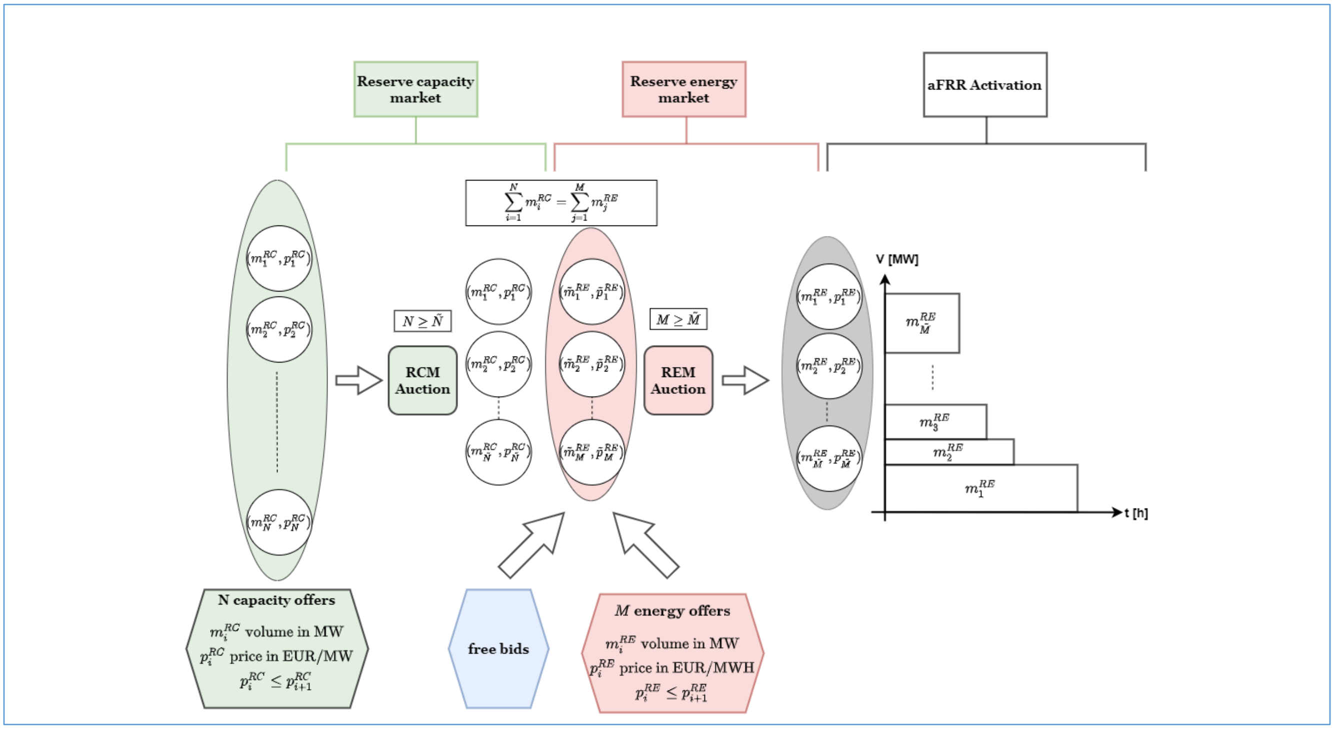

Figure 2: aFRR example auctions and activation for selected day and product. Bidding sequence of a BSP on the RCM and REM with potential aFRR activation.
First, a BSP places bids on the RCM (green). After announcement of the RCM auction results, the BSP is obliged to offer the total accepted amount on the REM auction (red). Furthermore, there is the opportunity to insert additional free bids as well (blue). Lastly, the accepted REM offers are potential candidates to be drawn for aFRR activation (grey). The sub-figure on the very right depicts the accepted REM offers in price-increasing order. Offered energy is activated in this order.

3. RESULTS

We restrict our study to observations from 04/2021 to 11/2021. In this period no changes in market design were made. The data needed for our study is made available by the TSOs. To compute the probabilities and auction results on the RCM we use [C]. For the calculation of expected activation duration of balance energy, we utilize [A, B].

To evaluate our bidding strategy, we compute a bid for every day in the data set. A bidder can offer 10 MW, for both positive and negative products. An example of a bid is shown in Table 1. In most cases there is only one offer per product. For the REM bids, we observe that a split of the available flexibility can be optimal due to the risk-averse strategy on the REM. Given these bids we compute the realized profits ex-post. For the RCM the realized profit is the sum of all bids that are lower than the marginal price for that day. For the REM, we compute the realized profit as in (3) with the observed duration instead of the expected activation durations.

Product	RCM POS	RCM NEG	REM POS	REM NEG
00_04	(100,10)	(25,10)	(85,10)	(45,10)
04_08	(225,10)	(250,10)	(85,3); (95,7)	(75,10)
08_12	(250,10)	(250,10)	(95,10)	(25,10)
12_16	(225,10)	(250,10)	(75,10)	(35,10)
16_20	(50,10)	(250,10)	(85,10)	(35,10)
20_24	(25,10)	(250,10)	(95,10)	(25,10)

Table 1: Example of the bidding structure (Price [€/MWh], Quantity [MW]) for the 05/05/2021.

Overall, the optimization results show an average daily profit of 14.084€ in the period from April to November 2021. For a more meaningful evaluation on the profits, we distinguish the profits between positive and negative products where an average realized profit of 1.483€ (POS) and 1.526€ (NEG) are made on the RCM and 10.790€ (POS) and 282€ (NEG) are made on the REM. In Figure 3 the daily profits of the four markets are shown. While the positive REM products are the main source of profit on most days, all markets exhibit strong increase in profit in October. This can be explained by an overall higher level in electricity prices in this month (cf. [1]). The distribution of the daily profits can also be seen in Figure 4. For all markets the profits can vary widely. For positive capacity and energy products a profit is made on most days. For the negative products the 25% quantile is near zero. Given accurate estimations of the acceptance probability in the RCM and the expected activation duration, as well as an appropriate range of price levels our bids should be optimal by definition. Therefore, we do not compare them to other bidding schemes. Instead, we compare the expected profits against the realized profits. A high error in this comparison means, that better schemes might be available while a low error hints at optimality. Table 2 shows that the average expected profit is reasonably close to the average realized profit for the RCM. In the REM we are systematically underestimating the possible profit in both for positive and negative products, since we rely on a risk-averse strategy here by optimizing against the worst-case scenario as pointed out in the section above. In Table 3 the actual activated volumes on the REM are depicted. We observed that the average daily activation differs fundamentally between the positive and negative REM. Whereas a mean volume of 93.63 MWh is activated on the positive REM, only a mean volume of 6.49 MWh is activated on the negative REM. This means, on average the BSP gets activated for roughly 87 MWh every day at a price of approx. 126€/MWh.

	RCM POS	**RCM NEG**	**REM POS**	**REM NEG**
Realized Profit (avg) [€]	1.483	1.526	10.790	282
Expected Profit (avg) [€]	1.608	1.493	9.380	249
Difference absolute	-125	33	1.410	33
Difference %	-8%	+2%	+15%	+13%

Table 2: Realized and expected average daily profits in [€] from 01/04/2021 to 30/10/2021 for both positive and negative energy on the RCM and REM.

	REM POS Volume [MWh]	**REM NEG Volume [MWh]**
Mean	93.63	6.49
25% Quantile	73.6	0.22
50% Quantile	91.76	1.45
75% Quantile	114.77	5.77

Table 3: Activated volumes [MWh] for both positive and negative energy on the REM and the corresponding quantiles from 01/04/2021 - 30/10/2021.

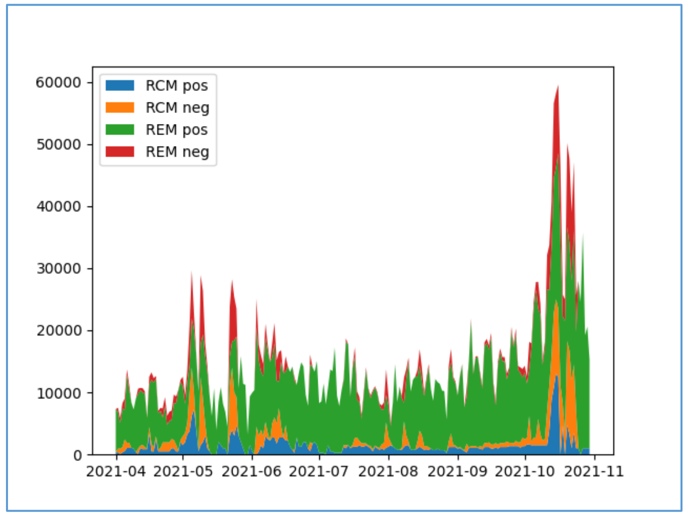

Figure 3: Daily realized profits from 01/04/2021 - 30/10/2021 for both positive and negative energy on the RCM and REM.

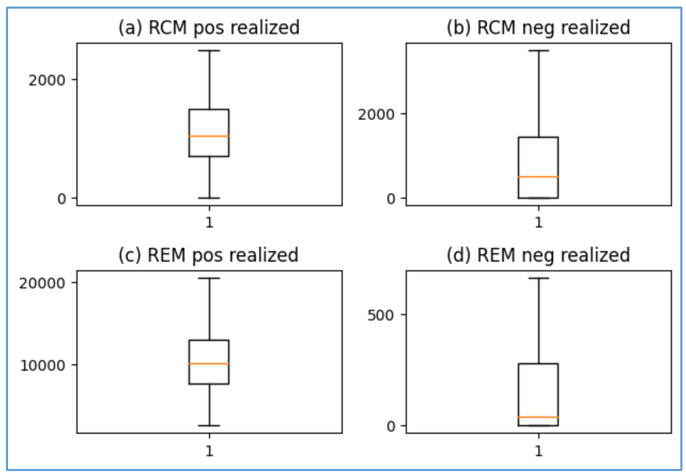

Figure 4: Boxplot of the daily profit distribution for RCM and REM for negative and positive products.

4. OUTLOOK

To harmonize national electricity balancing market designs towards a more homogeneous European structure, the European Commission has established guidelines on electricity balancing in [4]. With a clear objective to foster competition and to integrate the balancing markets into a European landscape, the ENTSO-E has launched the implementation project PICASSO to establish the European platform to the exchange of balancing of energy from aFRR [3]. The goal of PICASSO is not only a new data platform, but also a standardized market design for aFRR energy trading for all PICASSO member states. A substantial modification in the market design from a German perspective is the change from 4-hour aFRR products to 15-min products. Future research will incorporate these changes in market design to compute new optimal bids. While this paper focuses only on bids in the aFRR markets, the opportunity cost of bidding in these markets instead of the German intraday or the spot market needs to be considered. Finding optimal bids in the day-ahead, intraday and the aFRR market together is a natural extension of our framework that we want to examine next.

When we aim for a cross-market optimization of a battery as mentioned in the introduction, the question on the considered time horizon arises. In [6], it was observed that a planning horizon of more than a week yields better profits on the spot market. But, due to the technical constraints, the battery cannot be imbalanced over a longer period, i.e., it has to be in equilibrium within a given time horizon. With this in mind, we consider different time scales for these markets and therefore need a way to price the battery level. This should be done by incorporating expected future profits as well as the technical battery constraints and will be part of our future research.

ACKNOWLEDGEMENT

This work has been supported by the German Federal Ministry for Economic Affairs and Energy in grant 01186724/1 (FlexEuro: Wirtschaftliche Optimierung flexibler stromintensiver Industrieprozesse)

REFERENCES

[1] Braun, U., Frisch T., Oktober 2021: Regelleistung erzielt Höchstpreise, Webblog-post, Next-Kraftwerke, Last accessed on 10.05.2022 at: https://www.next-kraftwerke.de/energie-blog/steigende-preise-regelenergiemarkt-regelleistung

[2] ENTSO-E. (2018). EUROPEAN ELECTRICITY BALANCING GUIDELINE - An Overview of The European Balancing Market
Last accessed on 11.05.2022 at:
https://eepublicdownloads.entsoe.eu/clean-documents/Network%20codes%20documents/NC%20EB/entso-e_balancing_in%20_europe_report_Nov2018_web.pdf

[3] ENTSO-E. (2021). PICASSO - Platform for the International Coordination of Automated Frequency Restoration and Stable System Operation.
https://www.entsoe.eu/network_codes/eb/picasso/

[4] EU. (2017). Electricity balancing guideline. Official Journal of the European Union.
https://eur-lex.europa.eu/eli/reg/2017/2195/oj

[5] Kraft, E., Russo, M., Keles, D., & Bertsch, V. (2021). Stochastic optimization of trading strategies in sequential electricity markets (tech. rep.). Karlsruher Institut für Technologie (KIT).
https://doi.org/10.5445/IR/1000134346

[6] Leithäuser, N., Finhold, E., Heller, T., Schirra, F. (accepted, to be published). Optimal trading of flexible power consumption on the day-ahead market, Operations Research Proceedings 2021.

[7] Ocker, F., Ehrhart, K.-M., & Ott, M. (2018). Bidding strategies in Austrian and German balancing power auctions. WIREs Energy and Environment, 7 (6).
https://doi.org/10.1002/wene.303

[8] regelleistung.net,
Description of the balancing process and the balancing markets.
Last accessed on 21.05.2022,
https://www.regelleistung.net/ext/download/MARKTBESCHREIBUNG_CONS

[9] regelleistung.net,
Modalitäten für Regelreserveanbieter
Last accessed on 11.05.2022,
https://www.regelleistung.net/ext/download/Modalitaeten_02-11-2020_MfRRA

[10] regelleistung.net,
Prequalification for the provision and activation of balancing services
Last accessed on 11.05.2022,
https://www.regelleistung.net/ext/static/prequalification?lang=en

[11] Schäfer, P., Westerholt, H. G., Schweidtmann, A. M., Ilieva, S., & Mitsos, A. (2019). Model-based bidding strategies on the primary balancing market for energy-intense processes. Computers Chemical Engineering, 120, 4–14.
https://doi.org/https://doi.org/10.1016/j.compchemeng.201[.09.026

[12] Wagner, A., Ramentol, E., Schirra, F., & Michaeli, H. (2022). Short- and long-term forecasting of electricity prices using embedding of calendar information in neural networks. Journal of Commodity Markets, 100246.
https://doi.org/10.1016/j.jcomm.2022.100246

DATA REFERENCE

Source: regelleistung.net – Data Center
[A] SECONDS_BASE_AFRR_TARGET_VALUES (2021), Sekündliche SRL Sollwerte,
Last accessed on 10.05.2022 at:
https://www.regelleistung.net/apps/datacenter/activated-files/?dataSeries=GERMANY_aFRR_SETPOINT_MW_PT1S&cooperation=NRV&dateRange=2021-01,2021-12

[B] RESULT_LIST_ANONYM_ENERGY_MARKET_aFRR (2021),
Anonyme Angebotsliste Regelarbeitsmarkt,
Last accessed on 10.05.2022 at:
https://www.regelleistung.net/apps/datacenter/tendering-files/?productTypes=aFRR&markets=ENERGY&fileTypes=ANONYMOUS_LIST_OF_BIDS&dateRange=2021-01,2021-12

[C] RESULT_OVERVIEW_CAPACITY_MARKET_aFRR (2021), Ausschreibungsergebnisse Regelleistungsmarkt,
Last accessed on 10.05.2022 at:
https://www.regelleistung.net/apps/datacenter/tendering-files/?productTypes=aFRR&markets=CAPACITY&fileTypes=RESULTS&dateRange=2021-01,2021-12