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DOI
10.1016/j.enpol.2021.112522

Publication date
2021

Document Version
Final published version

Published in
Energy Policy

Energy Policy 158 (2021) 112522

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Making the most of short-term flexibility in the balancing market: Opportunities and challenges of voluntary bids in the new balancing market design

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A R T I C L E I N F O

Keywords:
Balancing market
Market design
Bidding strategy
Machine learning
Regulation
Market efficiency

A B S T R A C T

Electricity balancing is one of the main demanders of short-term flexibility. To improve its integration, the recent regulation of the European Union introduces a common standalone balancing energy market. It allows actors that have not participated or not been awarded in the preceding balancing capacity market to participate as voluntary bidders or 'second-chance' bidders. We investigate the effect of these changes on balancing market efficiency and on strategic behavior in particular, using a combination of agent-based modelling and reinforcement learning. This paper is the first to model agents' interdependent bidding strategies in the balancing capacity and energy markets with the help of two collaborative reinforcement learning algorithms. Results reveal considerable efficiency gains in the balancing energy market from the introduction of voluntary bids even in highly concentrated markets while offering a new value stream to providers of short-term flexibility. 'Second-chance' bidders further drive competition, reducing balancing energy costs. However, we warn that this design change is likely to shift some of the activation costs to the balancing capacity market where agents are prompted to bid more strategically in the view of lower profits from balancing energy. As it is unlikely that the balancing capacity market can be removed altogether, we recommend integrating European balancing capacity markets on par with balancing energy markets and easing prequalification requirements to ensure sufficient competition.

1. Introduction

To improve the efficiency of balancing markets and increase competition, the European Union (EU) has adopted a guideline that proposes significant changes to the balancing market design. Using an agent-based model (ABM[1]) with reinforcement learning (RL), we analyze the impact of these proposed market changes on bidder strategies and balancing market efficiency.

In order to maintain system frequency, European transmission system operators (TSOs) commonly procure balancing services through a two-stage process by first reserving the capacity in the balancing capacity market and then activating it as balancing energy when actual system imbalances occur. The need for new sources of short-term flexibility is growing as more conventional generation is being decommissioned and more variable renewables are coming online leading to rapid changes in residual load (ENTSO-E, 2019). Market design can create incentives for the entry of participants with new forms of flexibility (Poplavskaya and De Vries, 2019). This is relevant for balancing markets, in which the number of balancing service providers (BSPs) has been fairly limited because of strict prequalification procedures and long

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[1] In this paper, we use the following abbreviations: ABM – agent-based modeling, aFRR – automatic frequency restoration reserve, BC – balancing capacity, BE – balancing energy, BRP – balance responsible party, BSP – balancing service provider, CCGT – combined-cycle gas turbine, DA – day-ahead, EU – the European Union, FCR – frequency containment reserve, GCT – gate closure time, GL EB – EU Regulation establishing a guideline on electricity balancing, mFRR – manual frequency restoration reserve, TSO – transmission system operator, RES – renewable energy sources, RL – reinforcement learning.

https://doi.org/10.1016/j.enpol.2021.112522
Received 25 November 2020; Received in revised form 12 July 2021; Accepted 13 August 2021
Available online 25 August 2021

procurement timeframes (Poplavskaya and De Vries, 2019). The concentrated nature of balancing markets has long raised concerns about the high risk of strategic bidding[2] and market power[3] (e.g. Just and Weber, 2015; Poplavskaya et al., 2020a).

To improve the efficiency of balancing markets and increase competition, the EU guideline on electricity balancing (GL EB) introduced a common market for balancing energy, which, until now, was usually procured together with balancing capacity. A standalone balancing energy market allows a broader selection of BSPs to participate: besides bidders that were awarded in the balancing capacity market, other BSPs with flexibility available on a short notice may submit balancing energy bids as 'voluntary' bids (European Commission, 2017a). Besides, BSPs whose capacity bids were not awarded may still use the standalone balancing energy market as a second opportunity to make a profit.

This study investigates the implications of the new balancing market design, in particular:

- its effect on actors' strategies in the markets for balancing capacity and balancing energy and
- whether or to which extent voluntary bids can help increase market efficiency.

We inform decision-makers by analyzing the effects of regulatory changes on the pricing and availability of flexibility in the balancing capacity (BC) and balancing energy (BE) markets, on volume distribution among different marketplaces (balancing and day-ahead markets) and factors having an influence on this distribution. For this, we build upon the agent-based model of the BE market, Elba-ABM, introduced in Poplavskaya et al. (2020) by 1) developing a detailed model of the BC market, 2) linking it to the exogenous day-ahead (DA) market, 3) introducing voluntary bids in the balancing energy market. The main methodological contribution of this paper consists in the development of a novel collaborative reinforcement learning algorithm to model linked bidder strategies in the BC and BE markets.

The rest of the paper is structured as follows: the key references on the balancing market design and bidding strategies of BSPs are summarized in Section 2. The model of the balancing market, Elba-ABM, and the enhancements implemented to study the research questions are introduced in Section 3. In Section 4, we present the simulation scenarios and analyze the simulation results. In Section 5, we discuss policy implications of the research results and provide conclusions.

2. Background and literature

2.1. Brief overview of the structure of the balancing market in Europe

In the European networks, to offset frequency deviations caused by plant outages, unplanned changes in demand or in the output from variable renewable generation in real time, the TSO uses a stepwise procedure activating first the fastest frequency containment reserves (FCR) and, for larger deviations, frequency restoration reserves (FRR). The latter are further subdivided into automatic (aFRR) and manual (mFRR)[4] reserves. Based on the sign of the imbalance, either upward (procured in the positive market) or downward (procured in the negative market) regulation is performed.

The European balancing capacity markets loosely correspond to regulation reserve markets in the U.S., more specifically, in PJM, CAISO, ERCOT or NYISO[5] and a few other organized electricity markets whereas balancing energy markets correspond to so-called real-time markets (see e.g. Zhou et al., 2016). The biggest difference is that, in the U.S., day-ahead and real-time markets are co-optimized by the independent system operator (ISO) with the day-ahead markets using a security-constrained economic dispatch. In the EU, balancing markets are cleared by the TSO within their own control areas: normally, balancing capacity is procured ahead of the day-ahead electricity market to secure enough capacity for potential energy activation in real time (balancing energy market). The day-ahead electricity market, in turn, is cleared by nominated electricity market operators. In addition, the products in the US reserve markets vary significantly across different states both in terms of naming and technical properties.[6] After the adoption of the GL EB, the balancing products are required to be standardized across the EU countries.

2.2. Studies of the balancing market

Balancing markets do not exist in isolation but are part of a sequence of short-term electricity markets. They provide alternatives for the commercialization of flexibility, hence the links between them motivate the bidding strategies of BSPs and should be considered if we are to derive meaningful conclusions for the balancing markets. These interdependencies were analyzed in Hers et al. (2016), Just and Weber (2015), Maaz et al. (2017), Ocker et al. (2017) and Weidlich (2009a). For instance, Weidlich (2009a) used ABM to study the connection between DA, balancing energy market and the CO2 market, Ocker and Ehrhart (2017) described the relation between the balancing market volumes and the efficient design of the intraday market. In his research, Maaz et al. (2017) focused on the bidding in three sequential balancing markets for balancing capacity while CE Delft (2016) explored further interdependencies between balancing and intraday markets.

From the market participants' perspective, the balancing market presents an additional trading option for their flexibility, as long as they are prequalified to participate (Poplavskaya and De Vries, 2019). The DA market is the largest market that provides market participants with robust price signals. It is particularly relevant for the BC market, commonly clearing ahead of the DA market, as it determines the actors' opportunity costs (Poplavskaya et al., 2019a). The gate closure times (GCTs) of different marketplaces also determine whether non-awarded bids can be submitted elsewhere. The bidder can use available market information to form price expectations and to exploit arbitrage opportunities. Several researchers have shown that, unlike largely competitive DA markets, balancing markets offer different options for strategic behavior, such as orientation of bid prices to the highest bid in pay-as-bid auctions rather than to one's actual costs (Ocker, 2017). Furthermore, market participants may have incentives to oversupply or undersupply the market, taking profit of intertemporal dependencies among sequential markets (Poplavskaya et al., 2019a). Using large data sets, Just and Weber (2015) came to the conclusion that the German

[2] Any rational bidder follows a strategy in a market. In this context, however, under "strategic behavior" or "strategic bidding" we understand bidding to exploit market information and/or one's dominant market position in order to excessively profit from a given market.

[3] Market power is defined as "the ability to affect the market price" where "the effect must be profitable and the price must be moved away from the competitive level" (Stoft, 2002, p. 318). The study of market power is motivated by the repeated presence of unrealistically high prices for the balancing service at the times apparently unaffected by scarcities.

[4] Some EU countries such as France and Spain, also use replacement reserves (RR) to replenish the amount of the manual frequency restoration reserve (ENTSO-E WGAS, 2020).

[5] PJM – Pennsylvania-New Jersey-Maryland interconnection, CAISO – California independent system operator, ERCOT - Electric Reliability Council of Texas, NYISO – New York independent system operator.

[6] Such as Spinning and Non-spinning Reserves in PJM, Responsive Reserves in ERCOT, or Contingency Reserves in CAISO.

market design provides a possibility to exploit strategic opportunities between the DA and the balancing market. They further showed that pay-as-bid pricing intensifies the incentive from deviating from one's true costs. This result was also confirmed by Poplavskaya et al. (2020).

The behavior of market participants has been further shown to be affected by other factors, including the repeated nature of balancing auctions, incomplete information, (low) competition levels and their portfolio structures (Maaz, 2017). Perceived risk and uncertainty, for instance, are linked to a low bidding frequency for balancing capacity, a low product resolution, i.e. the number of hours the bid should be available for potential activation, and the volatility of balancing energy prices (Bublitz et al., 2014; Conejo et al., 2010).

2.3. *The effect of design changes on bidder strategies in the balancing market*

A look at historical prices makes the effect of market design changes on bidding strategies and therefore prices evident. A good examples of this illustrated in Fig. 1. It shows price developments in the German positive and negative aFRR markets, respectively. In 2018, as a result of the adoption of the disputed 'mixed-price calculation' (in Ger. *Mischpreisverfahren*), the BC market experienced a large price hike (Fig. 1, top) whereas a mirroring effect was produced for BE prices ((Fig. 1, bottom). The abrupt change in the bidding behavior was caused by the change of the scoring rule: instead of awarding the bidder based on the BC bid price alone, an additional weighing factor based on the BE bid price was introduced. Interestingly enough, the prices went back to 'normal' soon after the 'mixed-price calculation' method was abolished in mid-2019.

Although the number of bidders in the balancing market has increased in the last few years thanks to the entry new flexibility providers, such as aggregators,[7] it is still much more limited as compared to the short-term electricity markets. The reasons for this include strict prequalification requirements, sometimes drafted only for specific technologies to fulfil; a thus far limited amount of short-term flexibility and a complex two-stage market structure. A modular approach to determining barriers to entry in European balancing markets was presented in Borne et al. (2018). The market structure has been addressed in great detail in Poplavskaya and De Vries (2019), where the authors provided a framework for analyzing balancing market design and comparing it to the requirements introduced in the GL EB.

The implications of some of the upcoming design changes have been studied in Poplavskaya et al. (2019a) and in Poplavskaya et al. (2020a). The authors in Poplavskaya et al. (2020) demonstrated, among others, that the introduction of a standalone balancing energy market led to considerable efficiency gains in particular in combination with marginal pricing, yet was alone insufficient to protect the market from strategic bidding requiring additional adjustments (Poplavskaya et al., 2020a). Another arguably important market design adjustment is the introduction of voluntary bids in the BE market. Poplavskaya et al. (2019) used theoretical bidding calculus to study the impact of market sequences on the optimal bidding strategies of BSPs and observed that voluntary bids can significantly alter bidder strategies by altering the regular BSP's price and competition expectations and dampening market power.

2.4. *Research gaps and contribution*

Due to their novelty, the effect of voluntary bids has not yet been modelled or sufficiently studied in research. Voluntary bids as a design change in the balancing market have been marginally addressed, for instance, in Ehrhart and Ocker (2021) and Poplavskaya et al. (2019b). Ehrhart and Ocker (2021) and Poplavskaya et al. (2019b) provide a preliminary analysis of the impact of voluntary bids on balancing capacity costs based on a theoretical bidder calculus. The paper by Ehrhart and Ocker (2021) and Poplavskaya et al. (2019b) addresses voluntary (also called 'free energy bids') on the margins and rather uses a theoretical mathematical model to study market equilibria between the day-ahead and balancing markets. Neither of the mentioned papers use a simulation approach or model the balancing markets based on the design required by the GL EB.

Balancing markets have been subject of close scientific attention in the recent years, yet a large part of it was focused on optimizing the bidding strategies of market actors or individual technologies, i.e. on the perspective of individual participants (e.g. Algarvio et al., 2019; Guinot et al., 2015; Kumbartzky et al., 2017; Benini et al., 2018; Schäfer et al., 2019). From the perspective of the market itself, the research has been focused on national markets (e.g. Germany Koch and Hirth, 2019; Ocker and Ehrhart, 2017), the Netherlands (van der Veen and Hakvoort, 2016) or the Nordics (Herre et al., 2020)). To our knowledge there has not yet been a comprehensive model-based study of the new balancing market design, as prescribed by the GL EB.

This paper is intended to address the identified research gap and to contribute to the policy dialogue about the efficient balancing market design. It is pivotal for adequate system operation at the time when more sources of flexibility are becoming available from a wider range of technologies and providers (e.g. Burger et al., 2017), balancing procurement is getting internationalized and harmonized (European Commission, 2017b) and the task of system balancing is becoming more challenging (ENTSO-E, 2019).

This study contributes to the policy dialogue on efficient balancing market design through an innovative, powerful method to study the market and emulate agents' strategic behavior. To address the research questions posed in Section 1, we support our analysis with the results of an agent-based model, Elba-ABM, enhanced with reinforcement learning. The latter is used to model agents bidding strategically based on the available market information and own experience. To the authors' knowledge, it is the first study that uses an agent-based model with learning agents to analyze the effect of voluntary bids on the strategies and the relation between the BC and BE markets. It is also the first to develop a collaborative machine-learning approach to modelling bidding strategies in interrelated markets. It allows us to draw valuable conclusions about the ways to make the most of short-term flexibility while keeping the prices close to competitive levels and inform decision-makers about possible caveats of market design changes.

3. Methodology

To answer the research questions posed in this study, we adapt the simulation framework of Elba-ABM, balancing energy market model developed in Poplavskaya et al. (2020).

Agent-based modelling is a useful tool for modelling markets with low competition levels, such as the balancing market, as shown in Maaz (2017), Poplavskaya et al. (2020) and Weidlich (2009). We chose ABM in order to:

1) reflect all market design characteristics of the BC and BE markets and intertemporal links between them.
2) represent diverse portfolios and bidding strategies of market actors not bound by assumptions of perfect competition and foresight.

The *original* model focused on the representation of a balancing energy (BE) market alone. Its main goal was to study the effect of introducing a BE market with marginal pricing, independent of the BC market, as per the provisions of the GL EB. It was compared with the current balancing market design, where BSP submit BC and BE bids together (far) ahead of real time. Using Elba-ABM, bidding strategies of strategic and true-cost bidders were compared, given these design changes in terms of system costs and weighted average prices in the BE

[7] For an example of the list of prequalified BSPs, the reader is referred to the official webpage of the German TSOs, www.regelleistung.net.

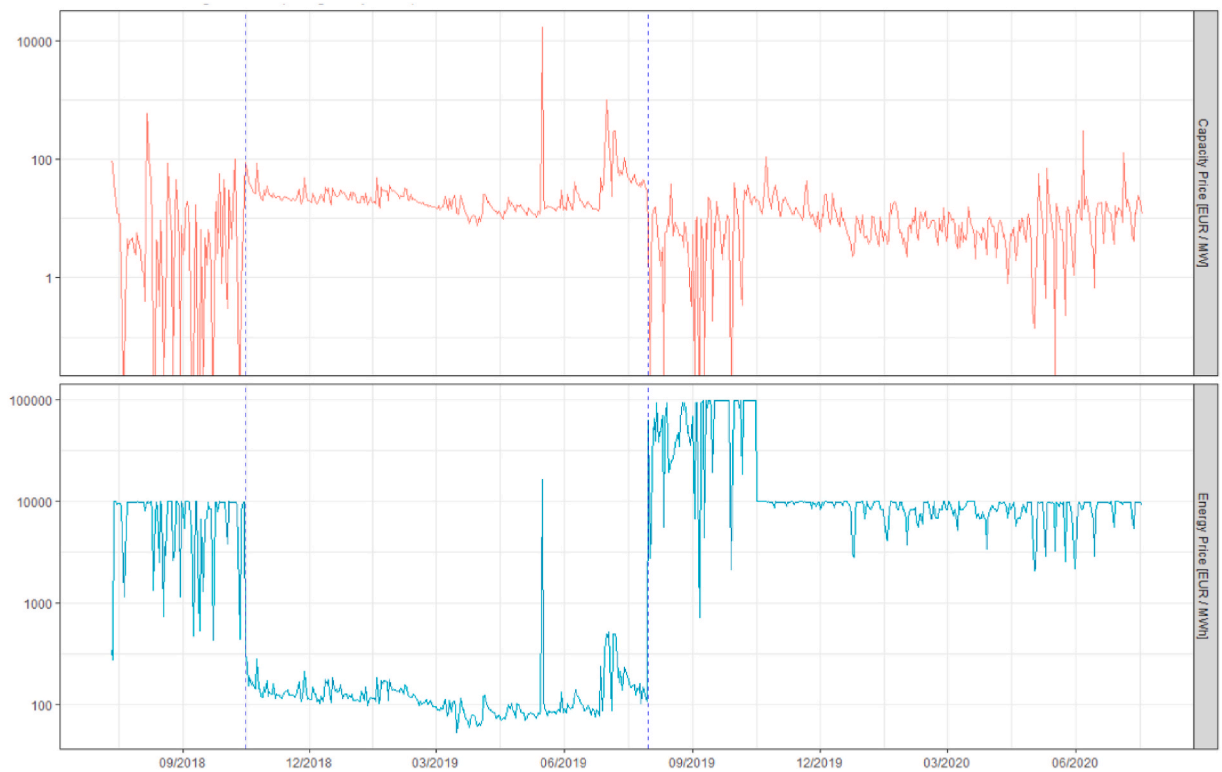


Fig. 1. The evolution of marginal prices for positive aFRR, balancing capacity (top) and balancing energy (bottom) in Germany from end of 2018 to mid-2020. The period during which 'mixed price calculation' was in force is marked with dashed lines. Please note that the logarithmic scale is used.

market. The BC market results were taken for granted, meaning that all bid capacity was assumed to be awarded, whereas BSPs could only compete on the BE price. The BE markets for upward and downward regulation were modelled and settled separately. The model did not consider the possibility of asymmetric bidding or the availability of voluntary bids. To illustrate the differences between the original and the new model, their characteristics are compared in a table in Appendix A.

In the *updated* Elba-ABM, a decision-making process with a larger scope is introduced as agents first compete both on volume and price in the BC market and then on balancing energy price in the subsequent BE market. Specifically, the market environment has been extended in the following ways:

1) It includes a detailed model of the BC market for upward and downward regulation with 24 hourly auctions per day each.
2) Asymmetric bidding is allowed: BSPs may submit different volumes and prices in the positive and negative BC markets for any given hour.
3) Positive and negative market are cleared in parallel, so agents cannot obtain updated information in one market to make a decision about the other, so they have to decide whether and how much to bid in both markets beforehand.
4) It accommodates the possibility to submit voluntary bids in the balancing energy market.
5) The day-ahead market is modelled implicitly by allowing agents to calculate their opportunity costs based on the expected DA market price for each hour of the next day using a naïve price forecast (see Section 3.2 for more detail).

Based on the BC market results, the set of participants in the BE market is always different. After the BC market is cleared, the agents are notified which generators and volumes have been awarded. This information is then passed on to the BE market, as is shown in Fig. 2. The awarded bidders commit their capacity in the BC market whereas the

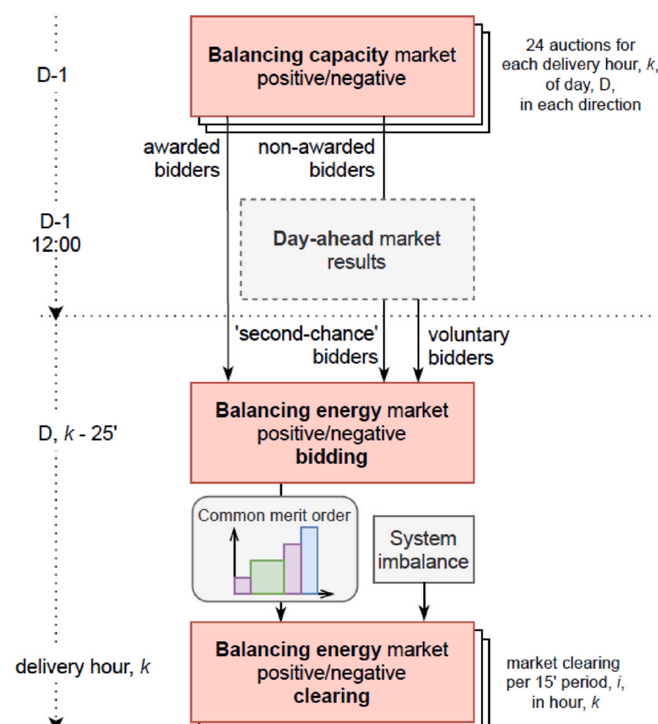


Fig. 2. Temporal flow between the balancing capacity and balancing energy markets and their links with the day-ahead market as well as three bidder types in the balancing energy market, regular bidders, 'second-chance' bidders and voluntary bidders.

non-awarded bidders may choose to participate in the BE market after the clearing of the DA market as 'second-chance' bidders. Finally, additional short-term flexibility in the BE can be provided by voluntary bidders who did not participate in the BC market. Then, a common merit order is built in the BE market clearing. The details of the model architecture and the extensions are graphically illustrated in Appendix B.

Participants in the balancing market are heterogeneous, some of them are price-takers whereas others bid strategically. The optimal bids of the latter are determined using reinforcement learning. Specifically, the agents in the extended Elba-ABM have been enhanced as follows:

1. Complex BSP bidding: agents can compete both on volume and on price taking the expected DA market price into account,
2. Two new agent groups, voluntary bidders and "second-chance" bidders, introduced,
3. Strategic bidders in the balancing market modelled with the help of reinforcement learning by representing them as two algorithms for one agent (one in the BC and the other in the BE market) that collaborate in order to maximize annual profits.

Model assumptions about the market and the agents are specified in Appendix C. Sub-sections 3.1 and 3.2 provide further details about the implementation of the extended Elba model on the market and agent levels, respectively.

3.1. Model extension: Balancing capacity market

The extended Elba-ABM model includes a detailed design of the balancing *capacity* market with the following characteristics:

- 48 daily auctions based on a predefined reserve requirement. The demand for BC is determined by the TSO and therefore fixed and inelastic.
- pay-as-bid settlement of awarded bids
- bidding *prior to* the gate closure time (GCT) of the DA market: the GCT of the BC market is D-1 at 8am. Daily bidding in the BC market with hourly products implies that market actors can submit up to 24 hourly bids in each direction for the next day.
- the minimum bid requirement is 1 MW.

A special procedure is introduced for situations in which the TSO could not procure a sufficient amount of balancing capacity to fulfil its reserve requirement: the TSO announces a second auction round in which all prequalified generators are obliged to provide their available capacity and the awarded power plants are remunerated on a cost-based basis.

The balancing *energy* market model (same as in the original Elba-ABM) follows the requirements of the GL EB[8]:

- BE bids are submitted in a standalone market close to real time,
- hourly BE auctions close 25 min before delivery,
- product duration is 1 h,
- awarded bids receive the uniform marginal price,
- voluntary bids are allowed.

3.2. Model extension: Agent design and bidder types

The agents' decisions in the BC and BE markets are linked to the expected prices in other short-term markets and to their variable costs (Poplavskaya et al., 2019a). Their bids are composed of three decision variables: the BC bid price per generator and hour, $p^{+BC}_{g,k}$, BC bid volume $q^{+BC}_{g,k}$ and BE bid price $p^{+BE}_{g,k}$ in the positive market (upward regulation) and similar decision variables in the negative market ($-BC$, $-BE$). BSPs submit BC and BE prices in separate marketplaces in different timeframes. The demand for BC, D^{BC}_{k}, is set by the TSO.[9] In the positive BC market, the generator bid is $b^{+BC}_{g,k} = \{p^{+BC}_{g,k}, q^{+BC}_{g,k}\}$, $k \in d$ and in the BE market: $b^{+BE}_{g,k} = \{p^{BE}_{g,k}, q^{+BE}_{g,k}\}$; in the latter, the bid volume is equal to the committed BC bid volume, $q^{+BC,\ awarded}_{g,k}$.

Agents bid differently in the positive and negative BC markets, as only the former involves actually producing energy. BC prices in the positive market are related to agents' opportunity costs per generator, i.e. the revenue forgone by not participating in other markets. Note that hydro power plants have low variable costs (1–2€/MWh, as assumed in (Weidlich, 2009, p. 153), which implies that they have high opportunity costs, as compared to gas turbines with high variable costs that mostly serve as peakers and have a much lower load factor. In the BE market, price-taker agents have no influence over the market outcome and bid at their short-term variable cost in the positive BE market $p^{+BE}_{g,k} = c^{var}_{g}\ \forall k$ while in the negative BE market, they bid up to their avoided variable costs as, i.e. willing to pay to the TSO. This is motivated by the fact that even if they reduce output, they still receive the revenues from the day-ahead market (Poplavskaya et al., 2020a).

Market actors may have different portfolios and strategies and decide on the bid volumes and prices individually per generator considering their variable costs and/or their prior experience. In the model, the choice can be made between two agent types:

1) *price-taking bidders* that bid their true opportunity costs in the BC market and, if awarded, bid their true short-term marginal costs in the BE market as would be expected under the assumption of perfect competition;
2) *strategic bidders* that attempt to maximize their profits based on market information and previous experience using a collaborative machine-learning algorithm. Since the balancing market is a two-stage process, reinforcement learning (RL) has been implemented as two collaborating agents in two different timeframes, daily (BC market) and hourly (BE market).

3.2.1. Link to the day-ahead market

Participation in the day-ahead market is implicitly considered in the model. An agent can sell its capacity either in the BC or the DA market or split it between the two. It is assumed that all agents are price-takers in the DA market, i.e. any volume is offered at their variable costs. To determine their opportunity costs, the agents in the BD market consider the expected DA market price that is calculated using a naïve forecast. It is based on the DA market prices of the day before prior to, during and after the delivery hour, k: $\{\lambda^{DA}_{d-1,\ k-2\ldots k+2}\}$, where $\lambda^{DA}_{d,\ k}$ is the market price on day d and hour k. We calculate the forecast error and the standard deviation of the forecast. Assuming a normal distribution of the forecast error, we use the confidence interval of 95% to obtain the lower bound, which determines the expected marginal price. It is assumed that each actor has the same price expectation for a given hour.

The trading options of market participants and, ergo, their strategies in the BC market depend on another factor, whether or not they are

[8] The GL EB further mandates that each standard balancing product in the future is procured in a single TSO-TSO balancing platform (European Commission, 2017a). However, for the sake of simplicity, this model assumes a single bidding zone.

[9] The demand for balancing capacity depends on the TSO's estimations and the bidding zone's generation and demand volumes. The demand for automatic frequency restoration reserve (aFRR) varies depending on the country size and the TSO's estimation of the biggest plant outage, etc. and can range between several hundreds to several thousands of MW. The demand of 200 MW is assumed in the simulation scenarios in Section 4 based on the demand of the Austrian TSO, APG, for aFRR.

expected to be infra or extra-marginal in the DA market, that is, whether their variable costs are expected to be below or above the DA marginal price (Müsgens et al., 2014). For instance, if an actor is expecting to be infra-marginal in the day-ahead market, he may decide not to bid in the BC market[10].

3.2.2. Voluntary and second-chance bidders

Actors that did not participate in the BC market, i.e. voluntary bidders, as well as 'second-chance' bidders, compete both on volume and on price in the BE market. Note that all voluntary bidders are assumed to be price-takers.

'Second-chance' bidders are those bidders that were not awarded in the BC market and, after the GCT of the DA market, evaluate if they take a second chance and participate by submitting voluntary bids to the BE market (see also Fig. 2). As the DA market is not modelled explicitly, it is assumed that if a generator's variable costs are below the actual DA marginal price, the generator's full volume was awarded in DA market. If that is the case, the agent bids the maximum available capacity in the negative BE market. Conversely, if extra-marginal in the DA market, the agent bids the maximum available capacity in the positive BE market.

3.2.3. Bid submission

In the BC market, the agents' action domain includes the following constraints for the BC bid volume in the positive and negative markets (based on Maaz (2017, p. 81):

$$q_{g,k}^{DA} + q_{g,k}^{+BC} \le q_g^{max}$$

$$q_g^{min} + q_{g,k}^{-BC} \le q_{g,k}^{DA}$$

where $q_{g,k}^{DA}$ is the *expected* volume in the DA market in a given hour.

Consequently, the bids submitted in the positive and negative market must validate the condition:

$$q_{g,k}^{+BC} + q_{g,k}^{-BC} = q_g^{max} - q_g^{min}$$

For the positive market, *opportunity costs* in a given hour, k, are calculated as follows (based on (Maaz, 2017, p. 81)):

$$c_{g,k}^{opp,+BC}\left(q_{g,k}^{+BC}\right) = max\left(\lambda_k^{DA} - c_g^{var},\ \frac{\left(c_g^{var} - \lambda_k^{DA}\right) * q_{g,k}^{min}}{q_{g,k}^{+BC}}\right)$$

where λ_k^{DA} corresponds to the *expected* price in the DA market and $c_{g,k}^{opp,+BC}$ corresponds to the opportunity cost of generator g in hour k in the positive BC market.

For a power plant that is likely to be infra-marginal in the DA market ($\lambda_k^{DA} > c_g^{var}$), the opportunity costs, $c_{g,k}^{opp,-BC}$, are the difference between the expected DA price and the plant's variable costs. An extra-marginal power plant, in turn, faces fixed operational costs equal to the minimum volume required for the plant to deliver the committed volume for upward regulation. Conversely, in the negative market, opportunity costs of each generator are given by:

$$c_{g,k}^{opp,-BC}\left(q_{g,k}^{-BC}\right) = \max\left(0,\ \left(c_g^{var} - \lambda_k^{DA}\right) * \frac{q_g^{min} + q_{g,k}^{-BC}}{q_{g,k}^{-BC}}\right)$$

An infra-marginal power plant has no opportunity costs in the negative market as it receives the DA price and does not face any costs for reducing its output. An extra-marginal power plant ($\lambda_k^{DA} < c_g^{var}$), should run at least $q_g^{min} + q_{g,k}^{-BC}$ in the DA market in order to provide downward regulation. If the expected DA price is lower than a generator's variable costs, it must still be able to reduce its output, i.e. it runs at $q_g^{min} + q_{g,k}^{-BC}$.

Positive and negative BC auctions are cleared simultaneously and the bid volumes depend on the expected DA market price.

For *price-taking bidders,* we assume a risk-neutral strategy, which translates into:

$$b_{g,k}^{+BC} = \begin{cases} \left\{c_{g,k}^{opp,+BC}, q_g^{avail}\right\}, & if \quad \lambda_k^{DA} < c_g^{var} \\ \{0, 0\}, & else \end{cases}$$

$$b_{g,k}^{-BC} = \begin{cases} \{0, 0\}, & if\ \lambda_k^{DA} < c_g^{var} \\ \left\{0,\ q_{g,k}^{avail}\right\}, & else \end{cases}$$

If a generator is extra-marginal, the price-taking agent will not bid in the negative BC market but will bid the maximum available capacity in the positive BC market at the generator's opportunity costs. Conversely, if the generator is infra-marginal, such an agent will place the maximum available volume in the negative BC market at a price of zero as it does not face any opportunity costs. At the same time, it will not bid any capacity in the positive BC market.

If the actor was not awarded in either the positive or negative BC auction, the maximum available capacity is bid in the DA market.[11] If he was awarded in the positive market, the DA market receives the difference between the committed positive volume and the maximum capacity of a generator. If awarded in the negative BC market, the maximum available volume is bid into the DA market[12]: $q_{g,k}^{DA} = q_g^{max} - q_{g,k}^{+BC,\ awarded}$.

For strategic bidders, two collaborating RL agents represent one market actor using a profit-maximizing strategy.

The BC market agent places two bids in the BC market per generator for each hour of the following day considering the available information in both markets. The RL agent in the BC market has two decision variables, the bid price and the bid volume, which have a significant effect on the action space. The level of discretization of the action space depends on the number of generators in the agents' portfolio. In order to limit the state-action space and the computational time and yet obtain meaningful results, the discretization of price actions is set to 7 and of volume actions to 4 per generator for a portfolio of three generators. This means that the combined discretized price-volume action space of an agent with three generators equals to 21,952 action pairs in each market time step. As a result, the agent can place either a markup or a markdown (also known as 'bid shading' (Ocker et al., 2018a)) up to its opportunity cost (i.e. bid up to maximum twice its opportunity costs). With regard to the bid volume, the bidder may bid 0%, 30%, 70% or 100% of the available capacity of a generator in its portfolio in the BC market.

For the training, the agent's model in the BC market is updated with the following information, separately for the positive and the negative markets:

3.3. Demand for balancing capacity

2) the agent's past bid prices and volumes,
3) past seven DA market and weighted average BC and BE market prices,[13]

[10] Note that this distinction has no bearing for the bids in the BE market as it takes place after the GCT of the DA market.

[11] Since the DA market closes *after* the BC market, then, if the bidder was not awarded in the BC market, he can either still bid in the DA market or, if voluntary bids are allowed, place a voluntary bid in the BE market instead ('second-chance' bidder).

[12] The volume submitted to the DA market is used only for reference purposes to identify the bidders' preferences.

[13] As bidders are remunerated pay-as-bid in the BC market, the TSO does not usually provide the information about the marginal price but rather publishes the hourly weighted average price.

4) profit from the DA market,
5) the hour and weekday of the bid.

It is assumed that if the BC volume bid is less than the total available capacity, the rest is bid in the DA market.

The BE market agent places bids in the BE market using the algorithm formulated in Poplavskaya et al. (2020). Similar to the BC market agent, we use a Q-fitted algorithm[14] to maximize the agent's cumulative reward over the entire portfolio and the episode (one year), based on the memory of previous market results and agent's own performance. Besides, as part of the dataset in the BE market, the agent now receives the volumes of capacities awarded in the BC market per hour and generator in its portfolio.

Together, BC and BE agents maximize the total reward for the strategic bidder. Different timeframes of the BC and BE markets create modelling challenges: the BC agent cannot otherwise quantify the expected reward and place an appropriate BC bid; it must assume that the BE agent is behaving optimally. Collaboration of the reinforcement learning algorithms is achieved in three ways:

1) through sequential training in the two markets,
2) sharing market information passed to the two agent's datasets,
3) sharing profits.

The profit of a BSP depends on whether the capacity bid was awarded and whether or not the committed capacity bid received an activation call. If the bid capacity was not included in the merit order for balancing energy (extramarginal BC bid), the BSP faces the opportunity costs for withholding capacity and the profit only includes the payment obtained from the amount, $q_{g,k}^{BC}$, of the bid volume multiplied by the bid price:

$$\pi^{BC} = \sum_{g=1}^{G} q_{g,k}^{BC} * \left(p_{g,k}^{BC} - c_g^{opp}\right) \forall\, k$$

Conversely, if activated, the overall profit is a sum of the two markets:

$$\pi^{BM} = \begin{cases} \pi^{BC} + \pi^{BE}, & if\ b^{BC}\ is\ awarded \\ 0, & else. \end{cases},$$

where

$$\pi^{BE} = \sum_{g=1}^{G} q_{g,k}^{BE} * \left(p_{g,k}^{BE} - c_g^{var}\right) \forall\, k$$

3.3.1. Training of the collaborative RL algorithm

Due to the fact that the agent's strategy in two interdependent balancing capacity and balancing energy markets are represented by two separate RL algorithms, their collaboration to form a coherent bidding strategy in all markets, among others involves consecutive training. That is:

- the algorithm for the BC market is trained in year 1 while the one in the BE market bids its true costs and all available volume;
- the strategy is reversed in year 2, during which the algorithm in the BC market bids optimally whereas the one in the BE market places random bids;
- In year 3, the algorithm in the BC market trains while the one in the BE market places optimal bids,
- In the final fourth year, both algorithms place optimal bids and we use those to evaluate the quality of the learned strategy.

[14] Interested readers are invited to refer to Lago et al. (2018) and Poplavskaya et al. (2020) for more details on the implementation of the learning algorithm.

This is necessary in order to ensure that the two algorithms do not interfere with each other's training process, i.e. keep the environment of each agent stationary.

During training, independently of the market, the agent follows an epsilon-greedy approach. It takes the optimal action with a probability of 1-epsilon, and a random action with a probability of epsilon. This is done as a tradeoff between exploitation and exploration (something required for RL training). As to the reward, both agents receive a reward that is proportional to the profits generated in both the BC and BE market. That is, despite the BC and BE agents being trained in different years, they all optimize the same reward function.

4. Scenarios and results

4.1. Description of the simulation scenarios

To study the effects of voluntary bids on bidding behavior, we analyze several scenarios in which the number of bidders is limited for two reasons. The first reason is methodological: increasing the number of participants would risk 'crowding out' the strategic bidder from the BC market, making the training less effective and, ergo, the results less conclusive. Second, an oligopolistic setting represents the 'worst-case' scenario, in which a change in market design can be expected to have the most benefit. Therefore, the scenarios contain three agents, each with a portfolio of three to five generation units. Each agent submits separate bids per generator submits to the positive and one to the negative balancing markets. The details of the agents' portfolios can be found in Appendix D.

The following three scenarios are defined:

1) *'all_TC'*: Baseline scenario with only price-taker actors (who bid their 'true-cost').
2) *'TC_&_SB'*: Scenario with true-cost bidders and one strategic bidder.
3) *'all_SB':* Scenario with three strategic bidders. In this scenario, a single true-cost-bidding agent is added that bids a high capacity price (300€/MW) as a proxy for scarcity situations in which the learning agents withhold balancing capacity.

Three variations of Scenarios 2 and 3 are analyzed. They include:

a) *'no voluntary bids'*: voluntary bidding in the BE market is not allowed,
b) *'+vol'*: the introduction of a single voluntary bidder with both cheap and expensive generation units who bids different – randomly chosen – flexibility volumes between 50% and 100% of the available capacity into the BE market.
c) *'+vol & second_chance':* in addition to a voluntary bidder, non-awarded BSPs may participate in the BE market as second-chance bidders (see also Fig. 2).

With the help of these seven scenarios, we trace the effects on the bidding strategies and on overall market efficiency based on market prices, total market costs as well as agents' profits. These simulations represent a close-to-real-life setup, in which actors do not have full information and have to make bidding decisions in several markets in different timeframes. The model therefore provides insight into possible consequences of different market designs and degrees of competition on actors' bidding strategies and the possibilities for market exploitation.

Observe that reinforcement learning is inherently non-deterministic, and the optimization function is non-convex, consequently, there could be multiple equilibria, making it difficult to say if the optimum is absolute or local. At the same time, we cannot guarantee an equilibrium in complex scenarios with multiple learning agents that influence each other and make the environment non-stationary. In such an environment, the model is unlikely to converge to a single equilibrium and the RL agents may not be equally successful. This is a general issue for multi-agent setups in reinforcement learning but also a more realistic way to model what happens in the real world. Our analysis should therefore be considered as a supplementary method for evaluating the risk of opportunistic behavior in complex, realistic settings.

By keeping a limited number of RL agents (up to three in our simulations), the agents have shown a good performance, i.e. managed to maximize their profits as compared to the previous years and to their counterparts with a true-cost strategy. Comparing the same scenario with the agents pursuing a true-cost strategy and then another one with the same agents with a RL strategy allowed us to pinpoint the differences in terms of bid price choices (and how often these deviate from the true costs), bid volume distribution and the profits. This approach helped us to improve the interpretability of the obtained results and demonstrate a satisfactory performance of the collaborative RL algorithm. The model has been further shown to yield valuable insights and to perform well within a reasonable computational time. It allowed us to develop new ways of capturing strategic behavior in the balancing market whose concentration has been demonstrated on multiple occasions (Just and Weber, 2015; Ocker et al., 2018b; Poplavskaya et al., 2020b).

4.2. Summary and discussion of the results

When analyzing the results, it is important to bear in mind the balancing market complexity. A bidder has an option to participate in the positive or in the negative BC market or split its available capacity between the two. The BE market is also split in two separate auctions. Agents' bidding strategies in the positive and negative BC and BE markets differ.

In the following, we highlight the main takeaways from the simulation scenarios, whereas all the results are summarized in Appendix E.

4.2.1. Results of the scenarios with no voluntary bidders

The price duration curves for scenarios *'all_TC'* and *'TC_&SB'* (a) to c)) are shown for the BC market in Fig. 3 and for the BE market in Fig. 4. This comparison demonstrates the extent to which the presence of a single strategic bidder in the balancing market can affect the market outcome, even considering market design improvements such as the introduction of a standalone BE market and the use of marginal pricing (as was discussed in Poplavskaya et al. (2020)).

In *'TC_&_SB'* scenarios, the strategic bidder can affect market results, which translates into higher market costs (for the TSO) as compared to the *'all_TC'* scenario. While the total BC costs increased from M€ 12 to M€ 19, the BE market costs are over three times higher (M€ 5,9 vs. M€ 18,8). Heim and Götz (2013) already found that the market outcome can be significantly affected by the actions of a single dominant supplier, leading, for example, to a dramatic decrease in market liquidity. A similar effect can be observed in Fig. 4 (orange line): the presence of a strategic bidder, roughly covering a fourth to a third of the total supply, leads to prices above 100 €/MWh ca. 10% of the time and to price spikes of almost 500 €/MWh. (In comparison, less than 2% of the time was all or nearly all supply needed to offset an imbalance.)

The agents' decisions in the BC markets are linked to their strategies in the BE market by the estimated likelihood of being called in the BE market and expected profits in both markets (Ocker et al., 2018a; Poplavskaya et al., 2019a). As a result, a strategic bidder may forego profits in the BC market to increase his participation in the lucrative BE market. Fig. 5 shows that in a scenario with *no voluntary bids* the strategic agent frequently bids close to its true costs. Notably, it also bids below its costs 16% of the time in order to secure its participation in the BE market. The incentive to participate in the latter is high: the profits of the strategic bidder in the positive BE market were 5,3 times higher than those in the positive BC market (M€ 0,5 vs. M€ 2,65, see Fig. 5, left).

4.2.2. Results of the scenarios with voluntary and second-chance bidders

This trend is reversed in the scenarios *'TC_&_SB + vol'* and *'TC_&_SB + vol&second_chance'*. The introduction of a voluntary bidder adds considerable price pressure on the incumbents in the BE market and

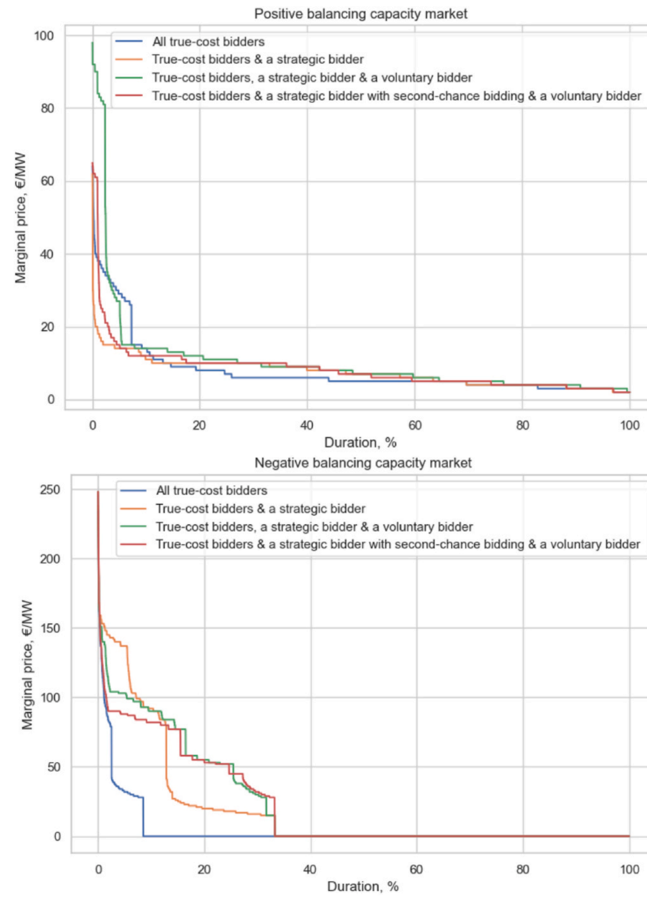


Fig. 3. Price duration curves in positive (top) and negative (bottom) balancing **capacity** markets, scenarios with all true-cost bidders and different bidder types.

reduces market power. It should be noted that we did not assume that the voluntary bidder's portfolio consists of only cheap generation (see Appendix D for agent portfolios). Voluntary bidders prompted more competitive behavior: the deviated from their true costs in the BE market only 20% and 11% of the time, respectively, as compared to 46% in the *no-voluntary-bids* scenario (Fig. 5). This led to a reduction of weighted average positive BE market prices of 72% in scenario *TC_&_SB* (see Appendix E). Simulations of the BE market for downward regulation produce similarly positive results (see also Fig. 6, right).

Even though second-chance bidders do not obtain revenues from the BC market (by definition), their presence in the BE market helps reduce the weighted average price and the total BE market costs further (Fig. 6, right). This can be explained by the intensified competition stemming from those bids that were initially filtered out by the BC market, where the TSO reserves a limited volume due to its high BC reservation costs.

4.2.3. The effect of voluntary bids on the balancing capacity market

Although the introduction of voluntary bids improves prices in the BE market, the same cannot be said about the BC market. As is illustrated in Fig. 3, the strategic agent almost never underbids its BC cost but bids higher more often when its participation in the BE market is no longer contingent on the outcome of the BC market (when second-chance bidding is allowed). As a result, the strategic agent (agent #2) increases its profits in the positive BC market and even more so in the negative BC market (see Fig. 6, left). Given dwindling BE profits, the RL agent maximizes profits elsewhere thanks to the collaborative learning algorithm. The negative market where it can earn profits from committing capacity to reduce output while also generating revenues in

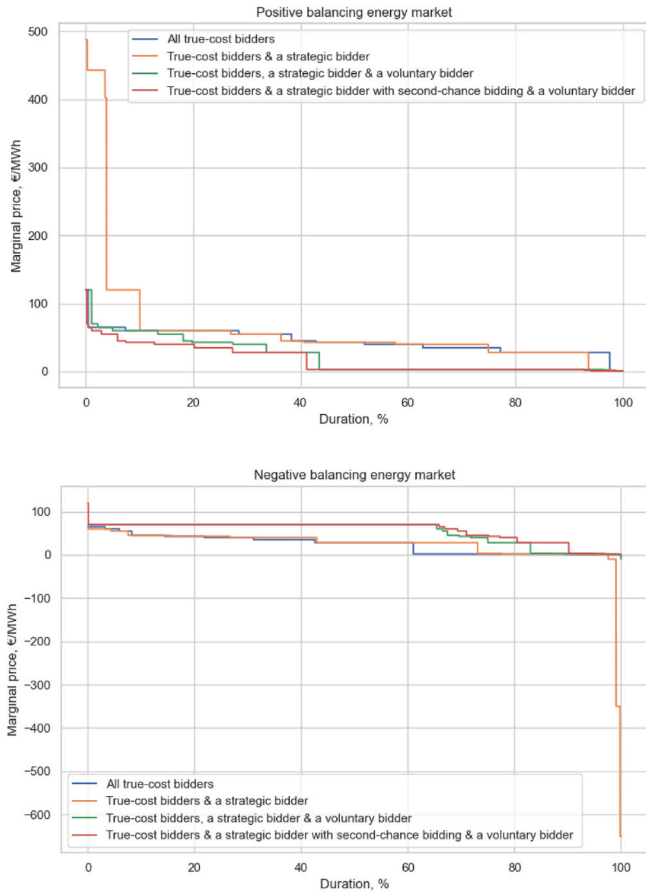


Fig. 4. Price duration curves in positive (top) and negative (bottom) balancing **energy** markets, scenarios with all true-cost bidders and different bidder types.

the DA market also proves to be more lucrative.

On the market side, the efficiency gains obtained in the BE market still outweigh the increased costs in the BC market. It should be kept in mind that negative amounts in the negative BE market indicate payments to the TSO.

If we assume that the balancing market is an oligopoly and all agents bid strategically (scenarios *'all_SB'*), a different picture emerges. All scenario variants produce extremely high yearly BC market costs in the model (between M€ 233 and M€ 54). These results, however, should be interpreted with caution. First of all, unlike true-cost bidders submitting all available capacity to the BC market, strategic bidders can choose how much to submit in the positive and/or negative BC market in order to generate more profit. As BC demand is inelastic, in order to ensure that sufficient capacity is procured at all times, an expensive backup bidder with a constant bid of 300 €/MW was introduced. In the simulations, it is used to signal scarcity in the market. However, as this bidder sets the price much of the time, this modeling choice influences the average prices in the model significantly. Strategic bidders optimize their profits over a total of four marketplaces, i.e. positive and negative auctions in the BC and BE markets. As a result, a large share of the BC market costs produced in these scenarios can be traced back to the back-up generator. Considering pay-as-bid pricing in the BC market and the model assumption that strategic bidders can bid up to twice their current opportunity costs, they cannot fully profit from the high prices generated by the backup bidder. Yet, they jointly push the price upwards and earn profits that by far exceed those in the *'TC_&_SB'* scenarios (see Appendix E). Learning effects in frequently repeated auctions (Ocker and Ehrhart, 2017), demonstrated in our results, allow strategic bidders to increase their profits substantially by learning from previous auction results.

Since in the BE market, the price pressure is still created by the voluntary bids, strategic bidders are compelled to moderate their bids and bid their true costs 46% (*'all_SB + vol'*) and 64% (*'all_SB + vol&second_chance'*) of all times, as compared to only 2% in the scenario with *no voluntary bids*. Similarly, a significant reduction is observed in the weighted average BE market prices (Appendix E). However, high concentration in the BC market raises the total costs to such an extent that they eclipse the gains from the BE market. In addition, similar to the *'TC_&_SB'* scenarios, in the presence of voluntary bidders, strategic bidders tend to shift most of their balancing capacity to the negative market. Remember that reinforcement learning algorithm i.a. considers the profits from the DA market (see Section 3.2.3) and, in this way, inframarginal generators maximize profits in the negative market while at the same time getting paid in the DA market.

4.3. Impact of introducing voluntary bids

The need for additional short-term flexibility is becoming more urgent as the volatility of residual demand and scarcity events are going to increase in the future. Voluntary bids benefit the balancing energy market, as set out in Section 4.2., as well as flexibility owners. Although participation in the BE market as a voluntary bidder means that they forego revenues from the capacity market, it provides additional flexibility for those BSPs that find it difficult to estimate their availability farther ahead of real time.

Such voluntary bidders are likely to have an impact on both the overall market and other bidders. Voluntary bidders with very low costs are likely to emerge, consider, for instance, aggregators of EV fleets. Yet, such bidders will also need to pass technical prequalification, so it would be unrealistic to assume that their entry into the balancing market would be massive or cheap across the board. For this reason, the impact of a single voluntary bidder with differently priced assets was studied. Considering that the balancing capacity market provides most of the

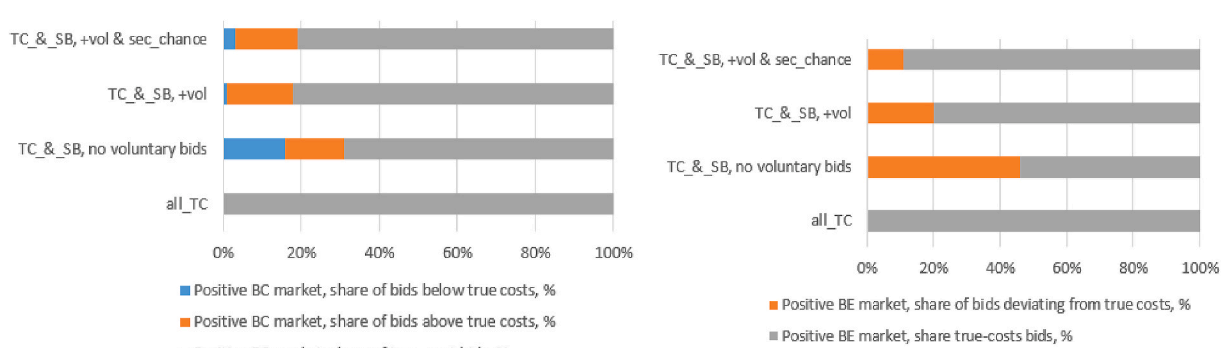


Fig. 5. The share of times the strategic agent bid its true costs or deviated from them over the year in the positive BC market (left) and in the BE market (right). The results for the negative market can be found in Appendix E.

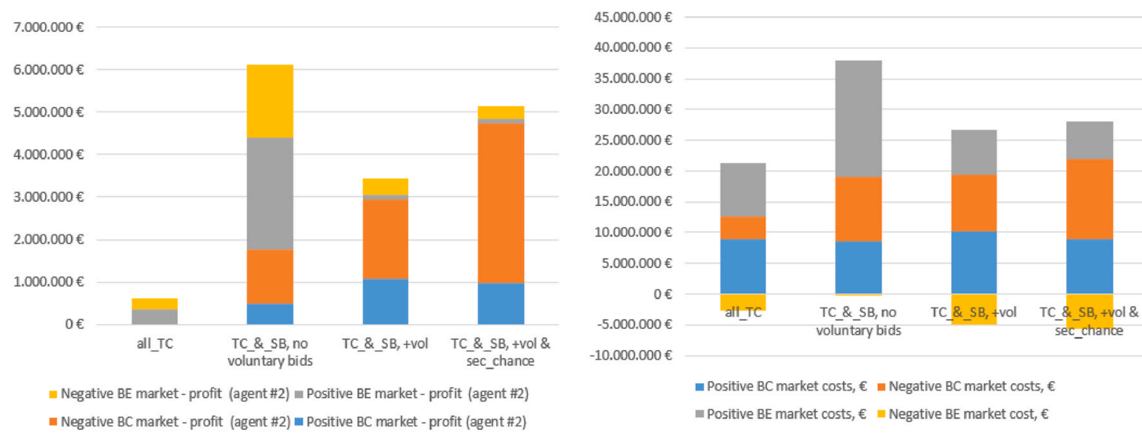


Fig. 6. Cumulative yearly profits of the strategic agent (agent #2) (left) and the total yearly BC and BE market costs (right) in the scenarios 'all_TC' and 'TC_&_SB'.

input to the balancing energy market, the introduction of voluntary bids does not eliminate but rather weakens the link between the two market stages. Reduced predictability and downward price pressure incentivize agents to bid closer to their true costs.

Second-chance bidding further improves competition in the BE market. Since the bids in the BC market are based on generators' opportunity costs as opposed to variable costs in the BE market, a bidder that was 'too expensive' in one market is not necessarily so in the subsequent market. An important implication is that the conditions for high market concentration are created by the BC market itself: only a few bidders are awarded since the volume of reserved capacity is both inelastic and limited. In particular, in smaller countries like Austria and the Netherlands, only a few hundred MW per product are procured (APG Austrian Power Grid, 2020; TenneT, 2020). However, higher volumes of procured balancing capacity would be undesirable in view of BC reservation costs that are mostly recovered directly through grid tariffs paid by consumers (ACER/CEER, 2017).

The scenarios included in the article assumed the presence of voluntary bidders (with or without 'second-chance' bidders) who introduce additional (and uncertain amount of) capacity into the balancing energy market and do not participate in the balancing capacity market. In such conditions and under the GL EB balancing market design, the market efficiency can be significantly improved. The Dutch balancing market that allows voluntary bids is a good empirical example of that. This relies on the premise that such new flexibility providers already entered the market and does not cover the transition period where that is still not the case.

The empirical evidence from Germany, where a standalone balancing energy market with a possibility to submit voluntary (or second-chance) bids was introduced in November 2020, shows that the presence of incumbent second-chance bidders only can lead to detrimental effects: market prices skyrocketed to tens of thousands of euros per MWh until the German regulator, Bundesnetzagentur, introduced a price cap of 10,000 €/MWh. In the first few months after such a significant change, we would expect few if any new entrants that, for instance, would still need time to prequalify. Secondly, such a change triggered an adjustment period where market actors were testing the new market's limits leading to high price volatility and some extraordinary price spikes.

Such transition phases are difficult to replicate with a computer model, however, the results of one more scenario, in which there no voluntary bidders but these are only the original agents that can place second-chance bids in the balancing energy market, were included in Appendix E, Table E2. As the simulation results show, such a setup leads to a detrimental result for both balancing capacity and energy markets as 1) agents no longer have an strong incentive to underbid their costs in the balancing capacity market (since it is no longer a prerequisite to participate in the balancing energy market) while 2) the prices in the balancing energy market increase as well. In this scenario, strategic bidders make the highest overall profits in both markets, which seems to have to do with the decoupling of the strategies in the BC and BE market and the participation in the BE market only depends on being awarded in the DA market. This result once again underpins the conclusion made in this article about the importance of enabling the entry of *new* flexibility providers in the balancing energy market.

Finally, the empirical results from the German market are further affected by other market design features that are not yet aligned with the requirements to the balancing market design set out in GL EB, making them less comparable to the simulated scenarios. The product length in the German aFRR and mFRR markets remained 4 h instead of 1 h and the pricing rule remained pay-as-bid instead of marginal pricing modelled in the scenarios in Section 4.2 and required by the GL EB.

In sum, short-term flexibility comes at a cost. Under the market design proposed in the GL EB, the cost shifts to the balancing capacity market. As our research shows, the extent of this shift largely depends on the degree of market concentration. Removing the BC market altogether as proposed in previous research (e.g. Just and Weber, 2015; Vandezande et al., 2010) could be a means to prevent existing distortions. Currently, removing the balancing capacity procurement appears feasible in the short run as it would entail a risk of a shortage of balancing energy.

Improving the conditions for new actors and technologies to participate, i.e. in the TSOs' prequalification procedures, is essential for improving competition in the balancing *capacity* markets. The results presented in this paper indicate that the work of improving balancing market design is far from over and the adjustment, harmonization and integration of the European balancing *capacity* markets are crucial next steps for ensuring cost-efficient balancing service procurement. They would not only increase the available pool of balancing capacity but also might allow a degree of demand elasticity, which would discourage strategic bidding.

5. Conclusion and policy implications

The design of an efficient balancing markets has gained importance both due to the ongoing market harmonization efforts and to the increasing shares of volatile renewables in European power systems. In the European Balancing Guideline adopted in 2019, the new target design for the European balancing energy markets was proposed and envisaged to improve market access for all types of flexibility providers and increase competition. We provide new insights into the implications of the balancing market design changes with a particular focus on 1) the links between the bidding strategies in the balancing capacity and energy markets and 2) on the introduction of voluntary bids.

By expanding the agent-based model of the balancing market, Elba-ABM, we demonstrate complex bidding strategies of balancing service providers that take the information from the positive and negative auctions in the balancing capacity and energy markets into account. The novel collaborative reinforcement learning algorithm developed in this paper represented interdependent bidder strategies in the two markets. For instance, we show that a strategic bidder learns to optimally distribute limited available capacity between the positive and the negative markets and to underbid its costs in the balancing capacity market in order to secure a place in the lucrative balancing energy market.

The efficiency of balancing energy markets can greatly profit from short-term flexibility: it does not only expand the TSO's options for handling system imbalances but also substantially reduces the market's exposure to strategic bidding. We show that the authorization of voluntary bids in the balancing energy market tends to reduce the cost of balancing energy procurement and compels strategic bidders to bid close to their true costs. Notably, this holds true even in the scenarios with highly concentrated markets with all strategic bidders. Furthermore, if bidders that were not awarded in the balancing capacity market can take a second chance by submitting a balancing energy bid, this leads to additional efficiency gains. The reason is that it allows to overcome the initial concentration caused by the balancing capacity market having a limited and inelastic reserve demand.

We warn, however, that, the authorization of voluntary bids is not a 'silver bullet' for reducing potential for strategic bidding in the balancing energy market, especially if the number of new flexibility providers remains limited. Strategy-wise, the balancing energy market remains linked to the balancing capacity market, a prerequisite for participation in the second, energy activation, stage. We show that the changes in balancing energy market design can shift possible strategic bidding to the balancing capacity market. In the face of falling profits in the balancing energy market, learning agents tend to pursue a more aggressive profit-maximizing strategy in the balancing capacity market. This may lead to much larger costs there and reduces the efficiency gains obtained in the balancing energy market through voluntary bids. We further show that this is particularly an issue in concentrated markets where decreasing profits from the balancing market risk to drive positive balancing capacity away from the market. Therefore, securing competition in the balancing capacity market, e.g. by allowing prequalification of new technologies and by integrating European balancing capacity markets, is of paramount importance to efficient balancing markets.

Future research should focus on modelling and studying the implications of balancing market integration as well as on further applications of reinforcement learning in electricity markets.

Data availability

All data used for resampling in the simulations presented in this paper can be found on the official website of the Austrian transmission system operator, Austrian Power Grid: https://tts.apg.at/emwebapgrem/startApp.do.

CRediT authorship contribution statement

Ksenia Poplavskaya: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, preparation, Visualization. **Jesus Lago:** Conceptualization, Methodology. **Stefan Strömer:** Software, Formal analysis. **Laurens de Vries:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

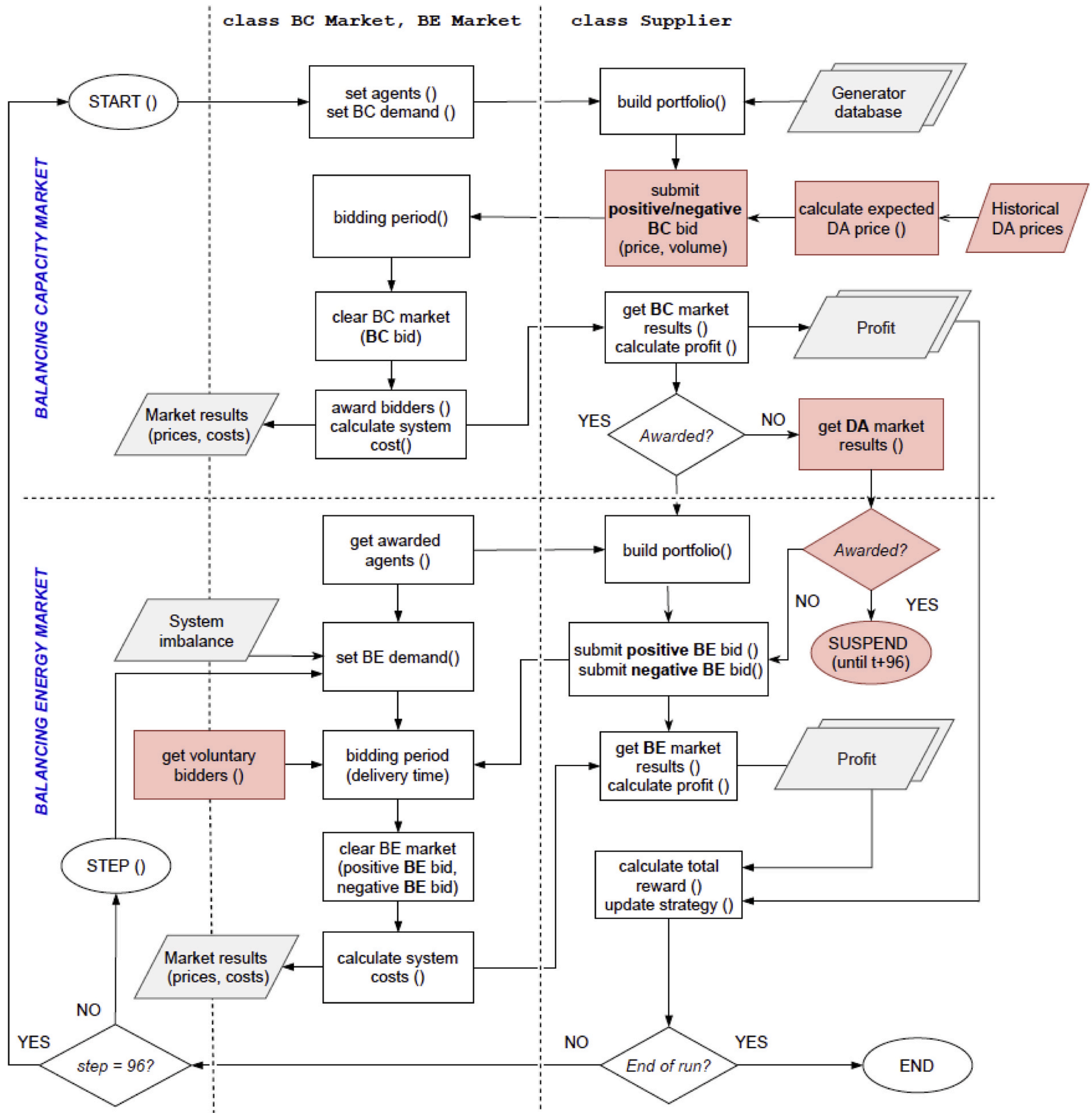
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Differences between the original Elba-ABM and the model presented in this paper

Model characteristics	Original Elba-ABM	Expanded Elba-ABM presented in this paper
Modelling of the balancing capacity (BC) market	yes, rudimentary, all participants are assumed to have been awarded	yes, detailed, implementing all design variables,
Bidding frequency (BC market)	n/a	daily with hourly products
Asymmetric bids	no, only symmetrical	yes
Pricing rule	n/a (profits in the BC market are disregarded)	pay-as-bid
Bid components	n/a	bid volume and bid price, separately for positive and negative BC markets
Link to the day-ahead market?	no, focus on the BE market	yes (day-ahead market is exogenous)
Reinforcement learning used in the BC market	no	yes
Modelling of the balancing energy (BE) market	yes, detailed	yes, detailed
Bidding frequency (BE market)	Hourly with 15-min market clearing	Hourly with 15-min market clearing
Pricing rule	marginal or pay-as-bid	marginal (as per the GL EB)
Bid components	bid price	bid price
Voluntary bids allowed	no	yes
Reinforcement learning used in the BE market	yes	yes
Portfolio bidding	yes, each agent has a different set of generators	yes, each agent has a different set of generators

Appendix B. Detailed flow diagram of Elba-ABM model

The model's balancing capacity market has been fundamentally elaborated to include multiple auction rounds in positive and negative directions. Besides, additional building blocks have been added to the model (marked in red) in order to establish a link between the BC market and the DA market and to allow 'second-chance' bidders and voluntary bidders.



Appendix C. Model assumptions

In the model, a number of assumptions were made about the market and the participants:

- There are several balancing products procured by the TSO, yet, in the model, it is assumed that participants can bid their available capacity only in the BC market for aFRR.
- To simplify, we assume that variable costs do not change over the simulation period and neither does plant availability (i.e. plant outages and maintenance are disregarded).
- Asymmetric bidding is assumed: BSPs can submit different volumes and prices to the positive and negative markets.
- All agents participating in the BC market are assumed to be prequalified.
- Technology-specific variable costs of the units in agents' portfolios are based on Elia Group (2019, p. 8).
- Four technologies are assumed to be able to provide aFRR, hydro, coal (as long as it is scheduled as a result of the DA market clearing), gas-fired power plants and combined-cycle gas turbines (CCGT). Unlike coal and gas turbines, hydro power plants do not have a minimum load requirement (Böttcher and Nagel, 2018, p. 192; Weidlich, 2009). For coal-fired power plants, CCGT and gas turbines, minimum load requirement is assumed to be static, 40%, 30% and 10% of the total installed capacity, respectively, based on Evangelos and Lehtilä (2016), Mielczarski (2018), Schill et al. (2016) (see Table A.1).

Table C. 1
Assumed marginal costs and minimum load requirements of the technologies used in the simulations.

Technology	Marginal cost, €/MWh	Minimum load
Coal	28-60 €/MWh	40%
CCGT	40-55 €/MWh	30%
Gas	60-82 €/MWh	10%
Hydropower	1-2 €/MWh	–

Appendix D. Agents' portfolios used in the simulation scenarios

Agent	Generator	Technology	Installed capacity, MW	Variable cost, €/MWh	Minimum load, %
Scenarios with true-cost bidders or with two true-cost bidders and a single strategic bidder					
1	a	hydro	70	1	–
(true-cost bidder)	f	coal	100	40	40
	g	CCGT	100	43	30
	j	gas	100	60	10
2	b	hydro	70	1	–
(true-cost or strategic bidder)	e	coal	100	35	40
	k	gas	100	65	10
3	c	hydro	70	2	–
(true-cost bidder)	d	coal	100	30	40
	i	CCGT	100	55	
	h	CCGT	100	45	30
	l	oil	230	120	10
Scenarios with strategic bidders					
1	a	hydro	60	1	–
(strategic bidder)	d	coal	120	30	40
	h	CCGT	120	55	30
2	b	hydro	60	1	–
(strategic bidder)	f	coal	120	40	40
	g	CCGT	120	45	30
3	c	hydro	60	2	–
(strategic bidder)	e	coal	120	35	40
	i	gas	120	60	10
4	j	oil	200	300	10
(true-cost bidder)	k	oil	200	300	10
Voluntary bidder portfolio					
	Generator	Technology	Installed capacity, MW	Variable cost, €/MWh	Availability
5	y	wind	40	3	50–90%
(true-cost bidder)	z	gas	60	60	50–90%

Appendix E. Summary of the simulation results

Table E.1
Summary of the simulation results showing total market costs, weighted average market prices as well as the degree to which strategic bidders deviate from the true-cost-bidding strategy.

	all_TC	TC_&_SB			all_SB		
		no voluntary bids	*+vol*	*+vol & sec_chance*	*no voluntary bids*	*+vol*	*+vol & sec_chance*
Positive BC market costs, M€	8,9	8,6	10,1	8,9	23,4	251,5	438,6
Negative BC market costs, M€	3,7	10,4	9,2	13,2	210,1	91,5	102,9
Total BC market costs, M€	**12,6**	**19,0**	**19,3**	**22,1**	**233,5**	**343,0**	**541,5**
Positive BC market - profit (agent #2), M€	0,0	0,5	1,1	0,9	5,8	1,7	1,9
Negative BC market - profit (agent #2), M€	0,0	1,2	1,8	3,7	1,2	14,6	15,8
Total profit BC (agent # 2), M€	**0,0**	**1,7**	**2,9**	**4,6**	**7,0**	**16,3**	**17,7**
Positive BE market costs, M€	8,6	19,0	7,2	6,1	23,3	6,4	5,3
Negative BE market cost, M€	−2,6	−0,04	−5,0	−5,6	7,5	9,2	−4,7
Total BE market costs, M€	**6,0**	**18,9**	**2,2**	**0,5**	**30,8**	**15,6**	**0,6**
Positive BE market - profit (agent #2), M€	0,4	2,6	0,1	0,1	9,3	1,6	1,2
Negative BE market - profit (agent #2), M€	0,2	1,7	0,4	0,3	6,7	3,2	0,6
Total profit BE (agent #2), M€	**0,6**	**4,3**	**0,5**	**0,4**	**16,0**	**4,8**	**1,8**
Total balancing costs, M€	**18,6**	**37,9**	**21,5**	**22,6**	**264,3**	**358,6**	**542,1**
Positive BC market							
Weighted average price, €/MW	7,7	7,5	10,1	8,2	31,0	294,0	249,0
Share of bids *below* true costs, %	0%	16%	1%	3%	27%	9%	17%
Share of bids *above* true costs, %	0%	15%	17%	16%	40%	47%	42%
Negative BC market							

(*continued on next page*)

Table E.1 (*continued*)

	all_TC	TC_&_SB			all_SB		
		no voluntary bids	*+vol*	*+vol & sec_chance*	*no voluntary bids*	*+vol*	*+vol & sec_chance*
Weighted average price, €/MW	4,7	19,1	23,4	21,9	242,1	81,0	112,7
Share of bids *below* true costs, %	0%	11%	8%	3%	28%	11%	19%
Share of bids *above* true costs, %	0%	3%	14%	13%	37%	46%	43%
BE market							
Positive BE market, weighted average price, €/MWh	53,0	115,0	44,5	33,0	130,0	39,0	32,0
Negative BE market, weighted average price, €/MWh	16,0	0,3	29,0	36,0	−42,0	−4,0	27,0
Positive BE market, share of bids deviating from true costs, %	0%	46%	20%	11%	84%	54%	36%
Negative BE market, share of bids deviating from true costs, %	0%	35%	32%	12%	98%	78%	60%

Table E.2
Simulation results of the scenario with only second-chance bidders in the balancing energy market.

	All_SB
	second_chance_only
Positive BC market costs, M€	340,7
Negative BC market costs, M€	72,6
Total BC market costs, M€	**413,3**
Positive BC market - profit (agent #2), M€	2,7
Negative BC market - profit (agent #2), M€	16,7
Total profit (agent # 2), M€	**19,5**
Positive BE market costs, M€	13,7
Negative BE market cost, M€	6,2
Total BE market costs, M€	**19,9**
Positive BE market - profit (agent #2), M€	3,2
Negative BE market - profit (agent #2), M€	5,6
Total profit BE (agent #2)**, M€**	**8,8**
Total balancing costs, M€	**426,3**
Total profit (agent #2), M€	**28,3**

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