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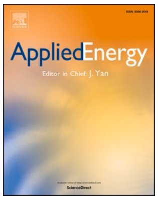

Economic evaluation of battery storage systems bidding on day-ahead and automatic frequency restoration reserves markets

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HIGHLIGHTS

- Implementation of reserves market in an agent-based electricity market model.
- Evaluation of battery storage bidding on day-ahead market and reserves market.
- Improved economic potential in German case study 2030 compared to 2019.
- Main source of revenues shifts from reserves market to day-ahead market.
- Highest revenues are found for short-term battery storages.

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ABSTRACT

In future electricity systems, not only electricity generation but also frequency stabilization must be provided by low-carbon technologies. Battery systems are a promising solution to fill this gap. However, uncertainties regarding their revenue potential may hinder investments. Therefore, we apply the agent-based electricity market model AMIRIS to simulate a day-ahead market and an automatic frequency restoration reserves market. Demonstrating the model setup, we chose a scenario with high shares of renewable energies. First, we back-test our model with historic market data from Germany in 2019. The simulation results' mean day-ahead prices of 39.20 EUR/MWh are close to the historic ones of 38.70 EUR/MWh. Second, we model both markets in a scenario for 2030. The simulated day-ahead market prices are higher on average than observed today, although, we find around 550 h/yr in which the load is fully covered by renewable energies. The variance in simulated prices is slightly higher compared to historic values. Bids on the reserve capacity market are derived from opportunity costs of not participating in the day-ahead market. This results in prices of up to 45 EUR/MW for positive reserve while the prices for negative reserve are 0 EUR/MW. Finally, we evaluate revenue potentials of battery storages. Compared to 2019, we see an improved economic potential and increased importance of the day-ahead market. High power battery storages perform best whereas improvements in round-trip efficiency only marginally improve revenues. Although demonstrated for Germany, the presented modular approach can be adapted to international markets enabling comprehensive battery storage assessments.

1. Introduction

Rising shares of fluctuating renewable energy (RE) ultimately lead to growing demand in flexibility options on various temporal scales. One prominent example is maintaining the frequency of power grids which is very sensitive to changes either in electricity demand or generation. There are various different mechanisms to ensure a stable frequency. In most countries, some kind of frequency restoration reserves markets are implemented to provide market-based system services. In Germany, for instance, the automatic Frequency Restoration Reserves (aFRR) – in combination with the Frequency Containment Reserves (FCR) and the manual Frequency Restoration Reserves (mFRR) – ensure frequency stabilization of the electricity system. At the moment, these markets are mostly supplied by conventional power plants and pumped hydro storages [1]. In future electricity systems, this may become a challenge, as

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Nomenclature

ABM	Agent-based electricity market model
AMIRIS	ABM developed at the German Aerospace Center
aFRR	automatic Frequency Restoration Reserves
BSS	Battery storage system
DA	Day-Ahead (market)
D_{spat}	Spatial differentiation
D_{tech}	Technical differentiation
D_{temp}	Temporal differentiation
E2P	Energy-to-power (ratio)
FCR	Frequency Containment Reserves
mFRR	manual Frequency Restoration Reserves
RE	Renewable energy
SOC	State of charge

there could be too little dispatchable capacity available. There are already discussions on the adaptation of the underlying power plant park and aFRR market design adjustments [2]. In theory, battery storage systems (BSS) are an attractive technology for maintaining grid frequency and participating in FCR markets and aFRR markets due to their short ramping times [3]. Hollinger, Diazgranados, & Erge [4] reviewed trends in the German FCR market concluding that the transition to distributed and renewable power plant infrastructure comes with opportunities for BSS under the assumption of higher volatility of day-ahead (DA) prices due to higher shares of fluctuating generation capacities. Nevertheless, there are currently hardly any significant BSS capacities providing balancing energy [1].

1.1. Regulatory and technical perspective

Policy-wise, the European Commission [5] provides a guideline for balancing the pan-European electricity supply system. This contains principles for reservation and accounting of several different frequency reserves. In addition, a uniform method for frequency reserve activation should be established. The regulation affects transmission system operators, distribution system operators, as well as the regulatory authorities of the EU member states. Ocker, Ehrhart, & Belica [6] modeled future auctions on balancing markets while taking into account the proposals by the European Union. The results show that those auctions with uniform pricing lead to systematic underbidding of market participants compared to the present pay-as-bid pricing due to the repetitive nature of the bidding by an invariant supplier side. Looking at the operator level, several studies have already assessed the implications and revenue potential of BSS in different energy systems and case studies. Thorbergsson, Knap, Swierczynski, Stroe, & Teodorescu [7] investigated the application of Li-Ion BSS providing FCR and compared several different control strategies varying the state of charge (SOC) set point of the BSS. A different analysis looking at the impact of multiple operation strategies for BSS providing FCR is conducted in Fleer & Stenzel [8] showing measures such as SOC limits have significant impact on the operation characteristics and therefore the expected revenues. A multi-use BSS is simulated in Zeh, Mueller, Hesse, Jossen, & Witzmann [9] calculating the economic benefits of additional aFRR market participation with only minor effects on the aging of the BSS. Braeuer, Rominger, McKenna, & Fichtner [10] conducted a comprehensive analysis of a BSS participating in the FCR market, intraday market, and DA market while providing peak shaving for small and medium sized enterprises in Germany. They found, that in all scenarios the net present values are negative concluding that it is economically not attractive under the scenario assumptions to invest and operate in BSS. Xu, Oudalov, Poland, Ulbig, & Andersson [11] looked at control strategies for BSS providing FCR and compared the situation in Germany with a selected market in the USA also finding a more profitable situation in the latter. Many more studies concerning BSS in DA markets and reserve markets exist, e.g. Tian, Bera, Benidris, & Mitra [12], Vejdan & Grijalva [13], Hu, Sarker, Wang, Wen, & Liu [14].

Flexibility cannot only be provided by BSS, but by various technologies. The most prominent one is pumped-hydro storage, such as described in Borsche, Ulbig, Koller, & Andersson [15], Doherty, Lalor, & O'Malley [16], Ela et al. [17], Kirby & Kueck [18], O'Sullivan, Power, Flynn, & O'Malley [19] and Wu, Lee, Cheng, & Lan [20]. There are studies on prosumers [21] which could also be active on reserve markets as presented in the case studies by Iria, Soares, & Matos [22] and Iria, Soares, & Matos [23]. Flexibility for the aFRR could also be made available by the aggregation of electric vehicles, as demonstrated in Ricardo J Bessa & Matos [24] and Ricardo Jorge Bessa & Matos [25] and Vatandoust et al. [26]. Other technologies are also investigated for their application for flexibility such as solar plants and BSS [27], gravity storage systems [28], hydropower [29], spinning reserves [30].

1.2. Modeling perspective

Modeling and evaluation of these applications has a long record in research. Important works have been conducted regarding the bidding on energy markets. Swider & Weber [31] present a methodology for actors bidding on multiple electricity markets under price uncertainty, explicitly including pay-as-bid reserve markets, by maximizing a stochastic non-linear objective function of expected profit. The specifics of sequential bidding in DA markets and reserve markets is addressed in Swider [32], whereas simultaneous bidding on the same markets is described in Swider [33]. Regarding the price mechanisms and interactions between DA markets and reserve markets, Chao & Wilson [34] present an assessment concluding that the separation of power bids and energy bids is essential for an efficient market design. Mazzi, Kazempour, & Pinson [35] look at bidding strategies in electricity markets where pay-as-bid remuneration schemes are implemented presenting a two-stage stochastic problem as a mixed-integer and linear problem. A fundamental analysis of the German balancing power markets is compiled in Müsgens, Ockenfels, & Peek [36] where the authors identify the scoring and settlement rules, which are based on the work of Chao & Wilson [34], as key elements of the market design. Loesch, Rominger, Nainappagari, & Schmeck [37] investigate the impact of energy prices in the German aFRR market on the probability of reserve energy activation and therefore the revenue potential based on historic market data from 2012 to 2016. Fleer et al. [38] analyze a BSS active on the German FCR market finding that the investigated bidding strategies do not have any significant influence on the profitability of BSS owners, whereas the development of FCR prices and BSS costs are crucial for the economic feasibility. The implementation of bidding strategies into models can be accomplished by several different techniques such as stochastic optimization [39], multi-stage stochastic optimization [40], probabilistic optimization [41], non-linear optimization [42], bi-level optimization [43], fuzzy optimization [44], evolutionary programming [45] and dynamic programming [46]. While most of these models apply some kind of optimization model, we use an agent-based modeling (ABM) approach. ABM puts the actors, their interactions and their environment to the center of the simulation. Thus, ABM allows for assessing the challenges of the energy transition taking the behavior of actors into account (Tesfatsion [47], Deissenroth, Klein, Nienhaus, & Reeg [48]). Additionally, ABM enables the researcher to look at the system's perspective and conduct analyses on energy system transformation pathways.

There are various studies investigating how future energy systems with a large reduction in green-house gas emissions could be achieved specifically taking into account the characteristics of BSS, such as Stiphout, De Vos, & Deconinck [49], Alqurashi, Etemadi, & Khodaei [50], Wierzbowski, Lyzwa, & Musial [51], Belderbos, Virag, D'haeseleer, & Delarue [52], Limpens, Moret, Jeanmart, & Maréchal [53].

However, they are missing the spotlight on the individual actor who is responsible for investing in new technologies, such as BSS. Investments in the energy system are characterized by significant expenditures resulting in long depreciation periods. It is therefore important to consider the perspective and revenue potential of an individual actor in order to estimate how investments in e.g. BSS could be refinanced on the markets. Existing literature mostly covers only a single market [54], small regions in remote areas [55], or peer-to-peer systems [56] when assessing the profitability of BSS. Different incentives for regulated versus market-driven BSS installations and their remuneration is described in Huang, Xu, & Courcoubetis [57].

1.3. Novelty of the present paper

The aim of this paper is to assess the economic potentials of a privately owned BSS which is active on the DA market and the aFRR market using synergies when serving both markets [58]. As described in the previous section, existing literature often applies different types of optimization models for analyzing wholesale electricity markets. In our opinion, however, such approaches cannot adequately account for the liberalized character of todays' electricity markets. Our fundamental electricity market model simulating the two markets and their interactions, therefore follows no overall objective function as used in optimization models. Instead, we can account for the outcome caused by the actions of individual actors participating in these markets which is much closer to actual market situations. Subsequently, the revenues and possible applications of a BSS operator in a future scenario will be determined and applied to a case-study simulating a whole market region rather than only a small test-region. An additional novelty of the present study is the combined modelling of the DA market and aFRR market following a model-within-model approach. This means that we integrate an optimization model for the revenue maximization of an individual BSS operator with a fundamental ABM simulation approach depicting the German electricity market. The two markets are explicitly modelled and the respective bidding and agent's behavior is implemented according to market theory described in detail in Section 2.1. Compared to the existing literature, our integrated assessment enables us to fundamentally model the market situation of future electricity markets. We derive the question of how the market situation is changing with increasing shares of RE and how it will affect the economic potential of BSS. Therefore, we set up a back-testing scenario and a future scenario in which agents participate on the DA market and aFRR market based on their marginal or opportunity costs, respectively. Hence, we simulate the prices on both markets. Subsequently, we evaluate the economic potential of BSS operators in order to assess their revenue potential. With some adaptations, the developed approach can be used to account for different market specifications and is therefore relevant for a wide international audience. The remainder of the paper is structured as follows. In Section 2, we describe our method and the data used. In Section 3, we elaborate the main findings consisting of the prices on the DA market and aFRR market as well as the revenue potential of a BSS operator on these markets. In Section 4, we compare our results with similar assessments in the literature and discuss the limitations of the presented approach. In Section 5, we conclude and give an outlook on future expansion and model developments.

2. Methodology and data

In order to investigate the market situation in a future energy system, we deploy two different kinds of models. The agent-based electricity market model AMIRIS simulating future electricity markets is presented in Section 2.1, whereas the linear optimization model depicting the BSS is described in Section 2.2. The back-testing scenario and the scenario for 2030 are outlined in Section 2.3 and Section 2.4, respectively.

2.1. Electricity market simulation model

The ABM AMIRIS [48] was developed to investigate the integration of renewable power plants in electricity markets. The behavior of individual prototyped groups of actors can be considered under different framework conditions such as varying market design or different remuneration schemes. In contrast to equilibrium and optimization models, there is no superordinate, centrally specified objective function that, e.g. minimizes system costs. Instead, the focus of the bottom-up model is on the actors of the electricity system represented as agents with their objectives and options for action. In AMIRIS, the relevant actors (e.g. direct marketers of RE plants or storage operators) are represented as prototypical agents [59]. Their microeconomic decisions are based both on the assessment of electricity market prices and generation forecasts. These are associated with uncertainties and the consideration of current support instruments for RE (variable and fixed market premiums or capacity premiums). The bids of the agents result in simulated market prices. For example, AMIRIS can be employed to examine the use of storage technologies in the electricity market from a business perspective. The central market in AMIRIS is the DA market, where an hourly market clearing of the power supply bids and demand bids is carried out resulting in simulated electricity prices. Conventional power plant owners place their bids with their marginal costs which are determined by fuel prices, CO_2 prices, technology-specific efficiencies and other variable costs. The DA electricity price results from the intersection of sorted supply bids and demand bids. A detailed description of the methodology of AMIRIS can be found in Deissenroth et al. [48] and Table A4. As elaborated in Section 1.3, we present a novel work of further developing and enhancing AMIRIS by the implementation of the aFRR market, which extends the possibility to generate revenues for the power plant operators. These actors can sell their flexible power generation either on the DA market or the aFRR market and aim to maximize their profit. The bidding behavior is fundamentally modeled and based on the technology-specific marginal costs of electricity generation. It is based on a theoretical comparison of the potential revenues on the DA market and those on the aFRR market [36]. Participation in the aFRR market is remunerated for reserving power (positive and negative) and for the actual provision of energy (positive if frequency below 50 Hz and negative if frequency above 50 Hz). The corresponding opportunity costs are calculated for the four products of the aFRR market (positive & negative power prices and positive & negative energy prices) as seen in equations (1) to (4). The calculation of the opportunity costs of the power prices requires an assessment of whether the power plant's offered output can be provided at prices less than or equal to the forecasted DA exchange price $\boldsymbol{p}_{forecast}$ (i.e. inframarginal state), or whether it must be generated at higher prices (extra-marginal state). The aFRR market bids are calculated as follows:

$$\boldsymbol{Bid}_{power,pos} = \begin{cases} \boldsymbol{p}_{forecast} - c, c \leq \boldsymbol{p}_{forecast} \\ (\boldsymbol{c} - \boldsymbol{p}_{forecast})^{*}\dfrac{\boldsymbol{Power}_{min}}{\boldsymbol{Power}_{pos}}, c > \boldsymbol{p}_{forecast} \end{cases} \tag{1}$$

$$\boldsymbol{Bid}_{power,neg} = \begin{cases} 0, c \leq \boldsymbol{p}_{forecast} \\ (\boldsymbol{c} - \boldsymbol{p}_{forecast})^{*}\dfrac{(\boldsymbol{Power}_{min} + \boldsymbol{Power}_{neg})}{\boldsymbol{Power}_{neg}}, c > \boldsymbol{p}_{forecast} \end{cases} \tag{2}$$

$$\boldsymbol{Bid}_{energy,pos} = \boldsymbol{c} \tag{3}$$

$$\boldsymbol{Bid}_{energy,neg} = 0 \tag{4}$$

With $\boldsymbol{Bid}_{power,pos}, \boldsymbol{Bid}_{power,neg}$ as the power bids for positive and negative aFRR in EUR/MW, $\boldsymbol{Bid}_{energy,pos}, \boldsymbol{Bid}_{energy,neg}$ as the energy bids for positive and negative aFRR in EUR/MWh, $\boldsymbol{p}_{forecast}$ as the forecasted DA market price in EUR/MWh, $\boldsymbol{c}$ as the marginal cost of generating electricity in EUR/MWh, $\boldsymbol{Power}_{min}$ as the minimum power generation of the power plant in MW and $\boldsymbol{Power}_{pos}, \boldsymbol{Power}_{neg}$ as the offered positive and negative

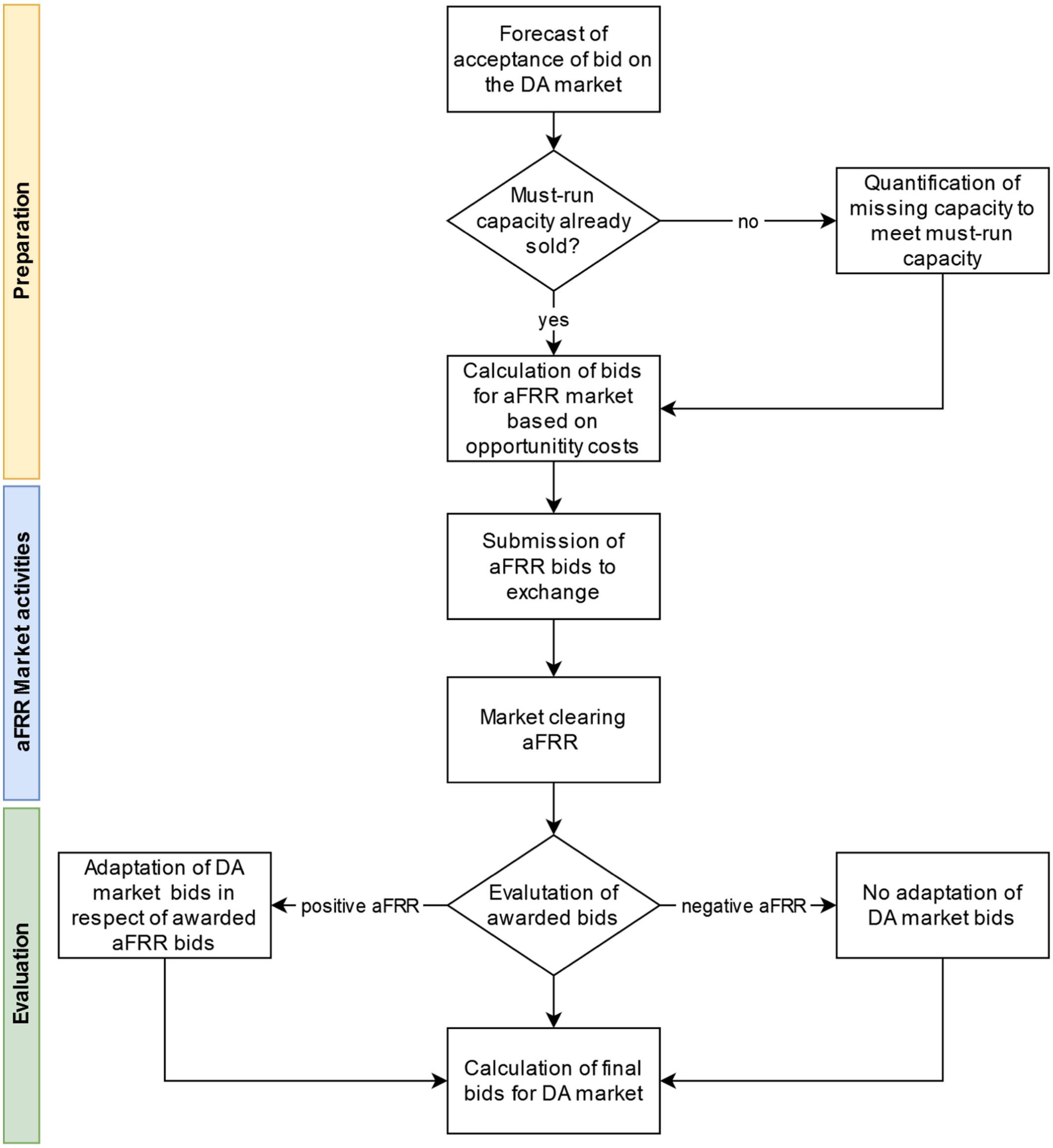

Fig. 1. Schematic bidding procedure of power plants participating in the aFRR market and DA market in the agent-based electricity market model AMIRIS.

power in MW used to determine power prices and energy prices.

The bidding logic process was implemented as shown in Fig. 1 and consists of three main phases: preparation, market activities and evaluation. In the beginning, the forecasts for the DA market are received. Based on the expected market participation, any missing capacity to achieve the must-run capacity is determined and results in bids at minimum prices to ensure that the must-run capacity is met. The aFRR bids are then formulated on the basis of equations (1) to (4). In the next phase, the market clearing of the aFRR market, both for the required positive and negative power, takes place. Once the bids are awarded on the aFRR market, they are evaluated in the final phase. This includes the adaptation of DA market bids corresponding to the awarded bids on the aFRR market in order to comply with the power plant's capacities. Final DA market bids are then forwarded to the DA market where a market clearing takes place determining the electricity prices. In the simulation, the described procedure is executed for each simulated hour.

Finally, the results of AMIRIS are price time series of the DA market and aFRR market depending on the available capacity of the technologies as well as the corresponding dispatch profiles of the power plants. These results are used in the optimization model as described in the following section. The presented electricity market model is currently representing the situation in Germany. However, it can also be applied to assess other international markets. This may necessitate minor adjustments in order to meet different market specifics, such as modifications to the market clearing mechanisms. The method of agent-based modeling and the object-oriented structure of the model enables researchers to accomplish the required changes with little effort.

2.2. Battery storage system optimization model

While the energy system model AMIRIS (Section 2.1) focuses on the electricity system from the system's perspective, we also set up an optimization model representing the market situation from the business perspective of a BSS operator. In other words, we apply a linear optimization model to evaluate the economic performance of a BSS in the presented scenario. The model is designed to find the optimal operation strategy of the BSS on the DA market and aFRR market under consideration of perfect foresight. The price time series are therefore used as input data in the optimization model. The BSS is constrained by technical specifications, such as charging and discharging efficiencies, ramping restrictions, and its state of charge. The optimization model is implemented as a mixed integer programming model in GAMS [60]

Table 1
Installed power plant capacities in Germany at the end of 2018 [62]

Technology	GW_{inst}
Nuclear	9.5
Lignite	20.9
Hard coal	23.8
Natural gas	23.8
Other non-renewable	10.1
Pumped hydro storage	9.7
Run-of-river	3.8
Biomass	7.7
Wind onshore	50.3
Wind offshore	5.4
PV	42.3

Table 2
Installed power plant capacities in the presented scenario for Germany derived from

Technology	Installed Power in GW
Nuclear	0
Lignite	9
Hard coal	11
Natural gas	53
Other non-renewable	5
Storage	8
Run-of-river and hydro storage	6
Biomass	6
Wind onshore	58
Wind offshore	15
PV	73

using the CPLEX solver [61]. It is assumed that the BSS is prequalified for trading on the DA market and aFRR market aiming to maximize its total revenue under perfect foresight over the observation period of one year. The function

$$Revenue_{Total} = \sum_{i=1}^{8760} Revenue_{DA,i} + Revenue_{aFRR,i} \tag{5}$$

describes the total revenues consisting of the summed revenues in hour *i* in the two markets which the storage operator tries to maximize. The revenues from trading on the DA market are defined by

$$Revenue_{DA,i} = p_{DA,i} {}^{*} (Energy_{DA\_Sell,i} - Energy_{DA\_Buy,i}) \tag{6}$$

with $p_{DA,i}$ as the price at the DA market, $Energy_{DA\_Sell,i}$ as the energy sold at the DA market and $Energy_{DA\_Buy,i}$ as the energy bought at the DA market in hour *i*.

The revenues from the aFRR consist, on the one hand, of the income from the provision of power $Revenue_{aFRR,Power,i}$ in positive or negative direction

$$\begin{aligned} Revenue_{aFRR,Power,i} = {} & p_{aFRR,Power,positive,i} {}^{*} Power_{aFRR,positive,i} \\ & + p_{aFRR,Power,negative,i} {}^{*} Power_{aFRR,negative,i} \end{aligned} \tag{7}$$

which are awarded with the prices $p_{aFRR,Power,positive,i}$ and $p_{aFRR,Power,negative,i}$ assuming that the BSS places its bids at the same price as the most expensive power plant which is still in the market; on the other hand, the revenue $Reveue_{aFRR,Energy,i}$ from the actual energy flows

$$\begin{aligned} Reveue_{aFRR,Energy,i} = {} & p_{aFRR,Energy,positive,i} {}^{*} Energy_{aFRR,positive,i} \\ & + p_{aFRR,Energy,negative,i} {}^{*} Energy_{aFRR,negative,i} \end{aligned} \tag{8}$$

which is awarded with the prices $p_{aFRR,Energy,positive,i}$ and $p_{aFRR,Energy,negative,i}$ when reserve capacities are actually called.By its specifications, the BSS is equipped with technical parameters that characterize its performance. First of all, the state of charge (SOC_i) must at no hour *i* fall below the minimum SOC_{min} or exceed the maximum SoC_{max} at any time. Accordingly, the following condition

$$SOC_{min} \leq SOC_i \leq SoC_{max} \tag{9}$$

applies for each hour of the optimization. Participating and trading on the DA market or the aFRR market has a direct effect on the SOC_i which is represented in

$$\begin{aligned} SOC_i = {} & SOC_{i-1} - Energy_{DA_{Sell},i} + Energy_{DA\_Buy,i} - Energy_{aFRR,positive,i} \\ & + Energy_{aFRR,negative,i} \end{aligned} \tag{10}$$

where the SOC_i is updated every time step *i*. At the beginning of the optimization, the battery is half charged. Additionally, a ramping condition depicted by

$$\forall Energy_i \leq \frac{SOC_{max}}{E2P} \tag{11}$$

applies. This means, that all energy flows $\forall Energy_i$, i.e. all purchases or sales on both markets, are subject to the maximum output rate. The energy-to-power (*E2P*) ratio indicates the charge or discharge in relation to its maximum capacity SOC_{max}. A BSS with an *E2P* ratio of 1 is fully charged in one hour from an empty state or can deliver full power for 1 hour, provided that it was originally fully charged. At an *E2P* ratio of 10, this would mean 10 h of charging or 10 h of continuous power. Therefore, the smaller the *E2P* ratio, the more suitable the storage is for short-term deployment. Battery degradation has not been considered in this model since the effect is expected to be very minor when interpreting the results of a single simulation year. Self-discharge has also not been considered in this work since the timescale of relevant self-discharge is in the order of months and thus much longer than the time interval of typical battery storage use in the order of days. A binary constraint prohibits the BSS from simultaneous charging and discharging in the same hour.

Finally, the optimization algorithm tries to find the best operating decision in each hour to maximize the operating result in the whole year

$$max\{Revenue_{Total} | conditions\ (9)\ to\ (11)\} \tag{12}$$

while considering the restrictions defined in (9) to (11). We do not consider other operational costs, taxes, costs of market participation, nor prequalification costs in the presented assessment. A description of the full parameterization of all input variables to the BSS model can be found in the Appendix in Table A7.

2.3. *Back-testing scenario 2019*

Back-testing is an important method for evaluating the outcome of energy systems models. That is why we have set up a reference scenario for Germany in 2019 in order to compare simulated prices to historic ones. The power plant park is listed in Table 1. Despite already high shares of RE plants in Germany, electricity generation is still dominated by fossil-based generators [62].

Historic electricity prices at the DA market, load data including imports and exports as well as RE generation are derived from the SMARD data platform which is hosted by the Bundesnetzagentur [63]. European Emission Allowances were taken from the EEX [64] and used for CO_2 price information. Fuel price indices are used from the monthly reports from the Federal Statistical Office of Germany [65]. The full list of model parameters is described in the Appendix in Table A5.

2.4. *Scenario 2030*

In order demonstrate the feasibility of the developed approach, we decided to define a case study for Germany in 2030. However, the model set-up can also be parameterized to serve similar international electricity markets. The presented scenario follows the results of the simulations in a study on the macroeconomic effects of the energy system transformation in Germany in Lutz et al. [66]. This study aims for an

Table 3
Capacities of technologies supplying the German aFRR market and total German aFRR demand as defined for the 2030 scenario

		Positive aFRR in GW	Negative aFRR in GW
Supply	Hard coal	0.2	0.2
	Lignite	0.1	0.1
	Gas	3.6	3.2
	Oil	0.4	0.2
	Hydro power	6.6	8.4
	RE (Wind/PV/ Biomass)	7.6	7.6
Demand	Total power requested	1.7	1.7

electricity system with almost 85% CO_2 reduction in 2050 compared to 1990 and describes a pathway to this goal. The power plant park was derived from the scenario year 2030. The structure of the power plant park is listed in Table 2. There are significant capacities of photovoltaics (PV) and wind power (onshore and offshore) installed. 60% of the yearly total energy demand of 539 TWh is supplied by RE technologies. A complete nuclear-phase out is already accomplished, whereas 11 GW of hard coal and 9 GW of lignite powered plants are still in service. The price for one ton of emitted CO_2 is defined at 35 EUR/t. The market premiums for RE are assumed to be variable under the current legal framework. Accordingly, the amount of the premium is adjusted monthly according to the market values of the respective technology.

An overview of all model-related assumptions and input parameters, such as fuel prices, specific emissions, power plant availability, economic factors and storage parameters can be found in the Appendix in Table A6 for the AMIRIS model and in Table A7 for the BSS optimization model.

In the presented market model, no electricity transmission grid is considered. Therefore, the regulation of generation plants is only based on economic principles and not caused by the grid restrictions. The net frequencies and the required power for frequency stabilization are not simulated, but are exogenously derived from historic data. We estimated the demand for positive and negative aFRR with 1.7 GW each which is based on historic averages for the German aFRR market [67]. For the supply side, the total capacity of each technology which participates in

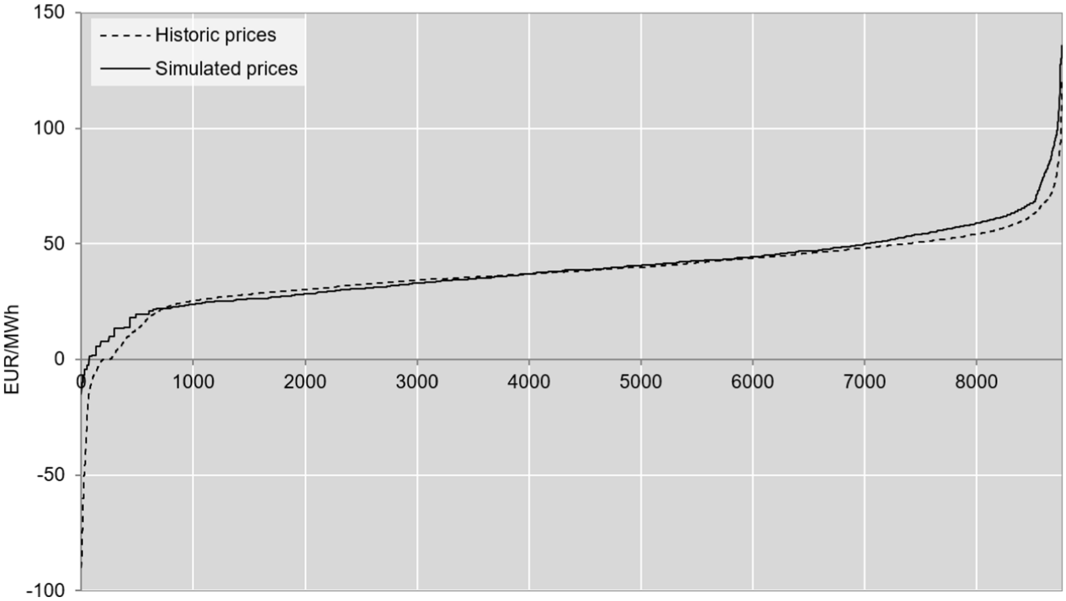

Fig. 2. Comparison of simulated and historic day-ahead price-duration curves.

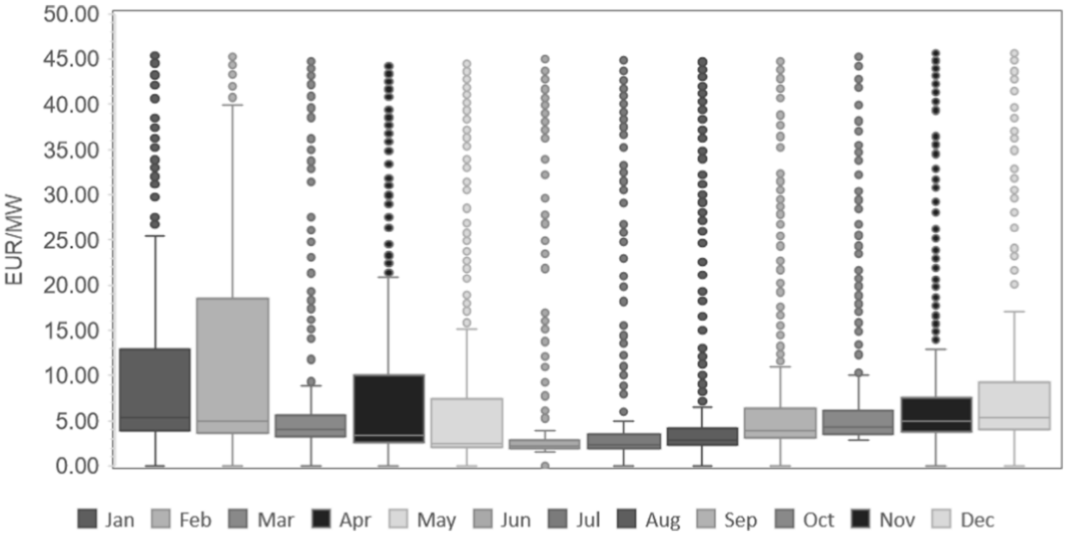

Fig. 3. Monthly positive aFRR capacity prices, showing the median, 1st, and 3rd quartile.

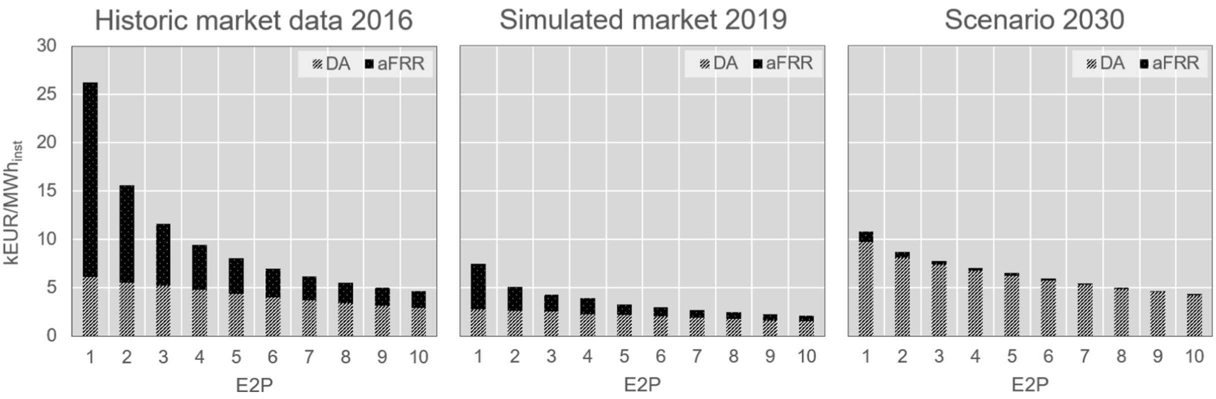

Fig. 4. Annual revenues per storage capacity of the BSS operator on the DA market and aFRR market based on 2016 historic market data (left), a simulated market for 2019 (middle) and the 2030 scenario (right).

Table A4
Model characteristics of AMIRIS; *D$_{temp}$, D$_{tech}$, D$_{spat}$ - temporal, technological, spatial differentiation.

Model name	AMIRIS - Agent-based market model for the investigation of renewable and integrated energy systems			
Author (Institute)	German Aerospace Center (DLR), Institute of Networked Energy Systems			
Model type	Agent based electricity market model			
Technical focus	Electricity market, use of renewable energies under regulatory framework conditions at actor level			
Geographic focus	Germany			
Spatial resolution	Single bidding zone			
Temporal resolution	Hourly			
Input parameters		D$_{temp}$	D$_{tech}$	D$_{spat}$
	• Costs (fixed and variable) for investment operators and direct marketers	x	x	
	• Power plant efficiencies	x	x	
	• General market conditions	x	x	
	• Fuel prices and CO$_2$ certificate prices	x	x	
	• Load profile	x		
	• Power plant park (conventional and renewable)	x	x	
Output parameters	• Profiles of storages under different operation strategies	x	x	
	• Profiles of RE plants under different regulatory frameworks	x	x	
	• Electricity prices	x		
	• Revenues of direct marketers	x	x	
	• Operational costs and emissions	x	x	

Table A5
Input parameters to the ABM AMIRIS in the back-testing 2019 scenario

	Parameter	Value	Unit	Note
Fuel prices	Nuclear	3.03	EUR/MWh	Federal Statistical Office of Germany [65]
	Gas	27.29	EUR/MWh	
	Lignite	5.00	EUR/MWh	
	Hard coal	7.86	EUR/MWh	
	Oil	30.70	EUR/MWh	
Specific emissions	Nuclear	0	tCO$_2$/MWh	
	Gas	0.202	tCO$_2$/MWh	
	Lignite	0.364	tCO$_2$/MWh	
	Hard coal	0.341	tCO$_2$/MWh	
	Oil	0.267	tCO$_2$/MWh	
Availabilities	Nuclear	85	%	
	Gas	97	%	
	Lignite	98	%	
	Hard coal	96	%	
	Oil	93	%	
Minimum and maximum efficiencies	Nuclear	33.0 – 33.0	%	Open Power System Data [81]
	Gas	27.6 – 61.2	%	
	Lignite	31.3 – 43.1	%	
	Hard coal	28.5 – 49.0	%	
	Oil	30.5 – 39.7	%	
Technical parameters of storage technologies	*E2P*	5	h	
	Charging efficiency	87	%	
	Discharging efficiency	87	%	
	Forecast period	168	h	
	Planning period	24	h	

the aFRR is shown in Table 3. We estimated the share of total installed capacities which can theoretically supply aFRR based on Hasche et al. [1] and for wind, PV and biomass from Spieker, Kopiske, & Tsatsaronis [68]. In the present market simulation, we have integrated an hourly bidding procedure. This is a simplification, since in reality on the German aFRR market, bids had to be submitted on a weekly, or – after changes in market design in 2018 [69] – daily basis. This adaptation had to be made in order to keep the problem solvable in the AMIRIS model. We expect, however, additional adjustments in the future which will likely introduce an even more short-term tender for the required aFRR.

3. Results

The following results are divided in Section 3.1 where we describe the outcomes of the back-testing of AMIRIS whereas in Section 3.2 we present the result of the scenario for 2030.

3.1. Results back-testing scenario 2019

The simulated and historic DA prices are plotted in Fig. 2 for the year 2019 as price-duration curve. When comparing to historic prices, we observe a higher price level for simulated prices. The mean price is 38.70 EUR/MWh for the historic prices and 39.20 EUR/MWh for the

Table A6
Input parameters to the ABM AMIRIS in the 2030 simulation scenario

	Parameter	Value	Unit	Note
Fuel prices	Gas	27.0	EUR/MWh	Lutz et al. [66]
	Lignite	6.0	EUR/MWh	
	Hard coal	9.0	EUR/MWh	
	Oil	112.5	EUR/MWh	
Specific emissions	Gas	0.202	tCO_2/MWh	
	Lignite	0.364	tCO_2/MWh	
	Hard coal	0.341	tCO_2/MWh	
	Oil	0.267	tCO_2/MWh	
Availabilities	Gas	97	%	
	Lignite	98	%	
	Hard coal	96	%	
	Oil	93	%	
Minimum and maximum efficiencies	Gas	27.6 – 61.2	%	Open Power System Data [81]
	Lignite	31.3 – 43.1	%	
	Hard coal	28.5 – 49.0	%	
	Oil	30.5 – 39.7	%	
Technical parameters of storage technologies	*E2P*	5	h	
	Charging efficiency	87	%	
	Discharging efficiency	87	%	
	Forecast period	168	h	
	Planning period	24	h	

Table A7
Input parameters to the BSS optimization model

	Parameter	Value	Unit	Notes
Time series	DA prices, historic 2016	Timeseries	EUR/MWh	Bundesnetzagentur [63]
	DA prices, from AMIRIS	Timeseries	EUR/MWh	
	Power prices aFRR market, historic 2016	Timeseries	EUR/MW	
	Power prices aFRR market, from AMIRIS	Timeseries	EUR/MW	
	Energy prices aFRR market, historic 2016	Timeseries	EUR/MWh	
	Energy prices aFRR market, from AMIRIS	Timeseries	EUR/MWh	
Technical parameters of BSS	Minimum SOC	0	MWh	
	Maximum SOC	1	MWh	
	Initial SOC	0.5	MWh	
	E2P	1–10	h	
	Charging efficiency	[92.20, 93.54, 94.87]	%	
	Discharging efficiency	[92.20, 93.54, 94.87]	%	
	Forecast	8760	h	
	Planning period	8760	h	

simulated ones. Especially for lower prices, AMIRIS tends to overestimate the prices. This effect can be explained by the fact that AMIRIS does not incorporate ramping and start-up costs of power plants in a bottom-up manner. Prices in the mid-range are simulated more accurately. In hours of high demand we find a higher level of prices in the simulation compared to the historic observations. The standard deviation is 10.60 EUR/MWh in the historic case compared to 11.50 EUR/MWh in the simulated scenario. The remaining deviations may be caused by costs for ramping power plants or due to missing depiction of block-bids in the current AMIRIS model. The correlation of the two price time series is 0.81.

3.2. Results scenario 2030

Besides the power plant dispatch, the main outputs of the AMIRIS model are the simulated price time series. Specifically, we derive a price time series for the DA market with 8760 h. The mean simulated DA price is 63 EUR/MWh. The price deviation is 12 EUR/MWh and therefore slightly higher compared to prices from 2015 to 2019 where prices deviated with 11 EUR/MWh around the mean of 35 EUR/MWh.

Fig. 3 shows the capacity prices in EUR/MW for positive aFRR as boxplots for each month of the modeled scenario year 2030. We have refrained from comparing the simulated aFRR prices with 2019, as the recent changes in German aFRR market regulations mean that this is no longer viable. Instead, as described in Section 2.1, we have applied the theory according to Müsgens et al. [36]. A high variability of aFRR prices can be observed in January, February, and April; whereas especially the summer months June, July, and August have the lowest mean and additionally the smallest deviation of prices. This effect may be explained by the interplay with the DA market where lower prices are usually also found in summer. The maximum prices are around 45 EUR/MW.

Regarding the negative aFRR capacity prices and following the theory of equation (2) described in Section 2.1, we observe prices of 0 EUR/MW. This means, that power plants with marginal costs below the forecasted DA market price can fully supply the negative aFRR capacities leading to this result.

In additional calculations, we altered the required demand from currently 1.7 GW to 2 GW in a “High demand” scenario, and to 1.4 GW in a “Low demand” scenario. These variations should account for the uncertainty of future aFRR demand and their effect on prices. However, these alterations did not change the prices significantly since the capacities are sufficient to meet the demand for the aFRR. Therefore, these results are not described in more detail.

While AMIRIS focuses on the whole electricity system, we can get insights in the situation for the BSS operator using our optimization model, which is described in Section 2.2. We use the price time series from the AMIRIS model as input to the optimization model and calculate the optimal BSS operation strategy. We assume that the BSS, which operates under perfect foresight, calculates its bids at the same price as the highest power plant which is still in the market. This leads to the identification of an upper limit regarding the revenue potential of the BSS operator. The results in the present scenario, however, disclose a very competitive situation on the DA market and aFRR market with overall low revenue margins for the BSS operator. Fig. 4 shows the annual revenues of a BSS on both markets with *E2P* ratios between 1 and 10 and a fixed roundtrip efficiency of 85% in three different situations. We compared the results from the presented scenario 2030 to revenue evaluations based on historic market data from 2016, and to the 2019 market simulations as presented in Section 3.1.

The analysis for the historic market data 2016 shows the highest annual revenues. Although the power plant park has not significantly changed from 2016 to 2019, we observe reduced economic revenue potentials in the simulated market 2019. This indicates that prices on the aFRR market are probably not fully described by the theory as stated by Müsgens, Ockenfels, & Peek [36], see Section 2.1, and the simulation is probably lacking to account for strategic bidding. The distribution of revenues between the DA market and aFRR market, however, is very similar. When looking at the situation in the scenario 2030 we find that total revenues are higher compared to the simulated market 2019, but still considerably lower than in the historic market data 2016 situation. Yet, the revenues from the DA market increase strongly until 2030 because of higher fluctuations in DA prices, leading to a major shift for the primary source of revenues towards the DA market in the scenario 2030. In other words, we hardly see any significant revenues from the aFRR market in the scenario 2030 since the BSS is mainly active on the DA market. The revenue split between the DA market and aFRR market is therefore significantly different in the 2030 scenario compared to the historic case (2016 and 2019). In the latter, the revenue share on the aFRR market ranges between 77% (for $E2P = 1$) to 27% (for $E2P = 10$) meaning that more short-term BSS generate more revenues from providing system services such as aFRR. The picture is different for the scenario 2030 in which we observe hardly any significant revenue from the aFRR market. This is contradictory to the study by Ela et al. [70] who state that system services may become a greater proportion of revenue sources.

Generally, assuming a fixed BSS capacity, the smaller the $E2P$ ratio, the higher the expected yearly revenues. This is caused by short-term fluctuations of prices which favor short-term BSS (smaller $E2P$ ratio). Calculations with different roundtrip efficiency levels showed that an increase in the roundtrip efficiency of one percentage point generates approximately 2.5% additional revenue for the BSS operator when operating on the DA and aFRR market.

Our results show a very challenging situation for BSS operators in the future scenario for 2030. Although the BSS operator acts under perfect foresight, one cannot expect revenue opportunities as observed in 2016. This low expected profitability may lead to reduced private investments in BSS. In case BSS are identified as an essential part of future energy systems [71] investors would need access to additional, more profitable markets or require further incentives to build flexibility options, such as BSS.

4. Discussion

4.1. Limitations of the modeling approach

The following points should be considered when applying the presented modeling approach and drawing conclusions from the results. First, the presented analysis does not consider all possible technologies for the provision of flexibility on the aFRR market, but uses only those listed in Table 3. For example, demand response or dispatchable loads of large consumers (e.g. industry) are not modeled. Similarly, there is neither Power-to-X nor a high penetration of electric vehicles implemented. Theoretically, these technologies expand the available capacity for frequency stabilization and could thus have an impact on prices at the DA market and aFRR market. However, they may require regulatory adaptations, which would allow them to participate at ancillary markets such as the aFRR market. Second, due to the downstream setup of the optimization model, the power supply of the modeled BSS has no influence on the coverage of the required quantity for frequency stabilization in the AMIRIS model. In the presented scenario, however, the simulated BSS has no system-relevant size. Therefore, we estimate the influence of the considered BSS operator as minimal on the change of the power prices. However, we do see the necessity of additional analyses in future work addressing the interplay of actors and their feedback on the prices. Regarding the implications of strategic bidding, Maaz [72] found that market participants add markups to their bids which can deviate from their marginal costs. Ocker, Ehrhart, & Ott [73] made an analysis of bidding strategies in the German and Austrian balancing markets, finding that the expected profits of the energy bid are taken into consideration for the calculation of the optimal power bid. Also Merten, Rücker, Schoeneberger, & Sauer [74] describe a comparison of different statistical approaches taking the acceptance probability of German aFRR bids into account. These issues may be addressed in future work to investigate the impacts on the prices and revenue potentials. Third, since the future demand for balancing power is very difficult to estimate, several variations of the required reserve power were assumed. However, only the quantity of required power, both positive and negative, was changed, but not the energy actually demanded. These quantities are difficult to project fundamentally, as they are very difficult to model and would require at least a basic implementation of the electricity grid, forecasting errors regarding load and generation as well as a representation of outages of power plants and power consumers. For these reasons, historic data on called energy is used for the analysis in this study. Fourth, the BSS in our test setup has access to the DA market and the aFRR market, as described in Section 2.2. However, BSS are also suitable for use in more short-term markets such as the Intraday market or FCR market due to their very fast response time [3]. However, these markets require a very high temporal resolution which currently cannot be modeled with AMIRIS. At the moment, we can conduct calculations on an hourly basis as described in Section 2.1. For this assessment, the aggregation of short-term markets to hourly values is not meaningful and would not achieve reasonable results. Alternatively, BSS can be active on mFRR markets competing with other large-scale power plants but also more innovative solutions such as virtual power plants or load shifting technologies in industry. The lack of these potential additional sources of income (FCR, Intraday, mFRR), however, could improve the economic situation in favor of the BSS operators. Fifth, the optimization calculation of the BSS is carried out under the assumption of perfect foresight. This means that the algorithm determining the BSS operation strategy has complete information, which is not available to this extent in reality. Therefore, the solver can calculate with market prices that will later occur exactly as expected. Additionally, we do not include taxes and levies on revenues or costs of market participation (e.g. prequalification costs for the aFRR market) for the BSS. Changes regarding the efficiency of the BSS showed no significant influence on the economic potentials. Furthermore, because cell degradation is driven primarily by calendar aging rather than cycle aging [75], we do not explicitly model this effect. In a long-term analysis of BSS, however, this has to be considered as a prominent driver in the economic evaluation. In general, we interpret the presented results as an upper-limit regarding BSS revenue potentials on the modeled markets. Finally, the lacking consideration of competition among the flexibility options should be mentioned. Such competition may lead to cannibalization effects and a further decrease of revenue potentials. The Europeanization of the electricity markets could also lead to more competition and greater pressure on individual operators in the markets and subsequently reduce the revenue opportunities of individual BSS.

4.2. Interpretation of the scenario 2030

The analysis by Braeuer et al. [10] is in line with our findings, as they conclude that investing in and operating BSS is not economically reasonable from a current point of view, despite they also considered multiple revenue possibilities. Berrada et al. [28] conducted a profit comparison between different storage technologies on DA markets and ancillary markets. Although their findings also show negative profits for innovative market participants – e.g. gravity storage – a valid comparison to our approach is not possible since they model only a single day whereas we simulate a full year. The analysis by Merten, Olk, Schoeneberger, & Sauer [76] investigates the combined use of BSS on the Intraday market and aFRR market concluding a potential economic feasibility of such systems in 2025. Angenendt, Merten, Zurmühlen, & Sauer [77] state solely the provision of frequency restoration reserve by BSS is less economical than a combined use with e.g. a PV system. The declining revenue potential for BSS over the last years is also found by Spodniak, Bertsch, & Devine [78]. Regarding different $E2P$ ratios, the findings by He et al. [42], Engels et al. [75] and Pusceddu et al. [58]

point in similar direction by showing largest revenue potentials for short-term orientated BSS and declining profits for BSS with higher *E2P* ratios. As Xu et al. [11] already proposed in their study, there is a need for adapting the regulations of existing ancillary markets, such as aFRR, to compensate for the specifics of BSS. Otherwise, a market-driven integration of BSS is not likely based on current regulations. Regarding the future demand for balancing power markets in electricity systems with high shares of RE, Ocker & Ehrhart [79] addressed the questions raised by Hirth & Ziegenhagen [80], concluding that the improvement of grid control cooperation can lead to significant efficiency savings. The situation in our 2030 scenario, however, is still very unclear and we cannot model the demand endogenously. According to the prequalified capacities for the aFRR market presented in Hasche et al. [1], we assume that a rising demand for aFRR could be met without any problems, even in a scenario with reduced conventional capacities. However, since the uncertainty regarding the demand remains, we investigated the effect of different demand levels for aFRR power in a sensitivity analysis. Yet, we did not find any significant changes in prices nor in the economic potential of a BSS. This is especially true for the scenario 2030, where the prevailing share is earned at the DA market. As described in Section 3.2, the technical specifications of the BSS in form of the *E2P* ratio have much greater influence on its total revenues. Therefore, we renounced to alter the scenario in this regard in more detail.

5. Conclusions

We present a novel approach for simulating the automatic frequency restoration reserves market alongside the day-ahead market in an agent-based electricity market model. For this purpose, we calculate bids based on the opportunity costs of market players in order to participate at the two modeled markets. First, the model was back-tested for Germany for the most recent available year 2019 achieving an overall good fit. Then, we have set up a scenario for 2030 according to a recently published study for a low-emission electricity system in Germany. The simulated electricity system features a significant share of renewable power plants supplying already 60% of the yearly electricity demand. From this scenario and model setup, we derive price time series for both investigated markets. We then assess the revenue potentials of battery storage system operators which are active on these two markets. In an optimization model, we calculate the optimal storage dispatch strategy and evaluate its profitability. When we compare the simulated potential revenues in the given scenario 2030 to those revenues in a simulated market 2019, we see an improved economic potential in the simulated future scenario. Additionally, in the scenario 2030 the distribution of revenues shifts towards the day-ahead market which is explained by higher price fluctuations. The technical specifications of the battery storage system are crucial for an optimal use-case. We find that the ability to provide power in the short-term leads to the highest revenues concluding that high power battery storage systems perform best in the given scenarios. Higher round-trip efficiency only contributes to minor improvements regarding the annual revenues. Additional calculations could further enhance the presented results by taking the investment and operational costs of battery storage systems into account. Future work may also improve the presented approach by including additional markets such as the Frequency Containment Reserves market or Intraday market into the model to generate a more comprehensive view of the revenue potentials. As discussed, the battery storage system operator may increase its revenue when employing a multi-use strategy to serve various markets simultaneously. While the presented modeling approach is demonstrated for the specifications of the German market, the developed methodology can be adapted to describe the situation on different national electricity markets such as North America or European countries. This enables policy makers, companies, and investors to get a better understanding of the application of battery storage systems. For this purpose, technical specifications may have to be adjusted to reflect the corresponding market design and rules. In addition, the region-specific power plant parks and market prequalification requirements to participate in the day-ahead market and frequency restoration reserves market must be considered accordingly.

Credit authorship contribution statement

Felix Nitsch: Conceptualization, Methodology, Software, Validation, Investigation, Visualization, Writing - original draft. **Marc Deissenroth-Uhrig:** Conceptualization, Methodology, Software, Writing - review & editing. **Christoph Schimeczek:** Validation, Investigation, Writing - review & editing. **Valentin Bertsch:** Writing - review & editing, Supervision.

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.

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Appendix

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