Journal of Energy Storage 21 (2019) 787–800

Contents lists available at ScienceDirect

Journal of Energy Storage

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

Bidding strategy for a battery storage in the German secondary balancing power market

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ARTICLE INFO

Keywords:
BESS
Batteries
Secondary balancing power
Secondary control reserve
Germany
Multi-agent simulation
Operating strategy
Bidding strategy
Secondary control

ABSTRACT

This paper develops strategies for operating Battery Energy Storage Systems (BESS) on the Secondary Balancing Power (SBP) market in Germany. Various control reserve market scenarios with participating BESS were simulated for the years 2016 and 2017. Within the simulation, the submitted bids of the SBP auction as a well as the BESS operation strategy have been optimized with regard to maximizing the economic revenues. The simulation makes use of an SBP power price prediction based on a SARIMA model and implements a battery model for lithium-ion batteries providing the aging status and an incremental cost breakdown for a specific operation strategy. With current battery and electricity market prices, the simulation reveals that it is not economically beneficial to provide SBP with a standalone battery. This is mainly due to the high requirements for SBP with respect to the power-to-energy ratio and operation strategy. The simulation further implies that a BESS operating in a pool is possibly economically viable as the restrictions for the power-to-energy ratio do not apply. The value of BESS in a pool is subject to the pool's precise configuration which prohibits a general statement regarding financial viability.

1. Introduction

To counter the threat of global warming and local air pollution, many countries are currently transitioning their electricity supply from centralized fossil fuel plants towards decentralized renewable energy plants. In Germany, the share of renewable electricity reached 33.9% of the total electricity consumed in 2016 [1]. The increasing share of intermittent (renewable) electricity generators combined with a continuous decommissioning of conventional power plants increases the need for auxiliary balancing services in the electricity grid. With the Climate Action Plan published by the German government following the Cop21 agreement, Germany pledged to reduce national CO2 emissions by 80–95% until 2050 [2]. This requires renewable sources to generate the bulk of electricity by 2050 and thermal power generation to be replaced.

If thermal and nuclear power generation is replaced, a new supplier for balancing services must be found as they currently provide the bulk of balancing services. Due to extremely fast ramp-up times, easily controllable output, and high efficiency, BESS are a potential candidate for the task and consequently a potential key-enabler of the energy transition. Currently, BESS already operate on the German Primary Balancing Power market. This paper develops and evaluates a bidding strategy for BESS on the SBP market. The proposed bidding strategy is based on an optimization approach maximizing the revenue of a BESS while considering battery aging effects. Historical market data is used for performance evaluation of the bidding strategy. Technical specifications of the battery system are taken from a real-life 5 MW /5MWH BESS constructed and operated by RWTH Aachen University [3].

This paper first explains the market framework in chapter II and the used data in chapter III. By analysing the literature available, an open research question is posed in chapter IV. The theory and methodology necessary to answer the question is outlined in chapter V. This includes a description of an SBP price prediction approach, the battery aging model used and an operating strategy of the BESS. Simulation results of historical market scenarios are presented in chapter VI. The paper concludes with a discussion of the results presented in chapter VII.

2. Market description and auction design

SBP (German: “Sekundärregelleistung”) is the second-fastest category of frequency restoring services after primary balancing power. Storage units such as batteries must be able to provide the contracted power for four hours (4-hours criterion). This can either be achieved by a standalone unit or by operating multiple units in a pool.

The SBP market in Germany is currently dominated by thermal power plants and hydro power plants representing approximately 97%

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https://doi.org/10.1016/j.est.2019.01.019
Received 21 May 2018; Received in revised form 17 January 2019; Accepted 18 January 2019
Available online 29 January 2019
2352-152X/

of prequalified power in November 2018 [4]. The high energy/ power ratio of 4 MW h/1 MW has prevented sizeable market entrances by BESS due to the high associated costs for battery capacity. Because of the limited market size of primary balancing power and the need for additional sources of income, BESS could in the future extend their activities to the SBP market.

This paper is developed under the regulatory system in place in Germany until summer 2018. The rules used are explained in the following: The SBP market operates in a two-stage process: Prequalified parties can submit a bid consisting of a power and an energy price. The power bid in €/MW relates to the cost for making the capacity available. Out of all bids, the cheapest power bids are accepted up until the power deemed sufficient for the safe operation of the system is reached (merit order). The energy bid in €/MWh relates to the cost of delivering energy. Both components of the bid are pay as bid. When SBP power is required in the grid, the transmission system operators (TSOs) distribute the request amongst all successful participants according to the merit order of energy bids.

The bids are submitted for four different product types: NegNt, NegHt, PosNt, and PosHt. The negative products ("Neg") represent a power reduction or an increased consumption. For positive products ("Pos") the opposite is true. The second parts of above abbreviations refer to the delivery time where Ht is delivered Monday to Friday from 8 A M till 8 PM. Nt covers the remaining time.

3. Data base

To aid bidders in deciding for a suitable bid, the TSOs make various datasets available on the website www.regelleistung.net. The data used in this paper includes:

- The anonymized successful bids of previous auctions
- The past average power provided in each quarter-hour
- Required balancing power on a quarter-annual basis

4. Literature review

Various authors have analysed both, the topics of BESS providing balancing power as well as the SBP market design in the past.

In a future scenario with little thermal or nuclear generation, a host of alternative technologies have been analysed in numerous studies including power2gas (H_2 and CH_4), pumped hydro, conventional power plants, biomass power plants, compressed air energy storage, combined heat and power, demand side management (especially heating and transport), BESS and many more [5]. In most scenarios, BESS are used to manage short-term fluctuations in the primary and sometimes secondary balancing power sector.

As the idea of BESS participating in the SBP market is relatively new, little research exists regarding the topic. For the British Market [6], derived an optimization strategy for various storage technologies working either as stand-alone or in conjunction with a wind farm. While offering ancillary services triples the battery profits compared to solely operating as arbitrage device, they find that the current revenues do not suffice to profitably construct and run a BESS. For the German case [7], state excessive costs for battery energy capacity as the main reason for the non-viability of battery storage systems providing solely SBP. According to them, the reason for these high costs are associated with the long minimum operating times due to the 4-hour criterion [8]. Falling battery prices [9] or new concepts such as using second-life batteries from electric vehicles [10–12] promise to overcome this issue in the near future and can provide cheap batteries for stationary, grid-connected BESS [13]. show that for primary balancing power, which is characterized by a higher power to energy ratio and much faster reaction times, there is an economic scenario for second-life batteries from electric vehicles. RWTH's BESS (M5bat) for instance currently generates revenue providing primary balancing power [3].

Overall, BESS could become viable on the SBP market in the future, but little research exists, particularly for the German market. [7] only state that cycling costs are too high without mentioning details. Authors from industry have followed a similar line of argument [14]. As part of their analysis [15], analysed SBP for an individual BESS but did not derive generic strategies. The author thus identifies a gap in literature where no numeric and in-depth analysis of BESS in the SBP market could be found.

4.1. Research question

Following the observations presented in this chapter, the following research question is distilled. The main question is split into four subquestions which collectively allow for answering the main research question in a numerical fashion.

Q: How economical are BESS on the SBP market?

Q1: What is the possible revenue given perfect foresight on balancing energy demand?

Q2: What are the economically most impactful aspects of operating a BESS on the SBP market?

Q3: Which SBP products are most attractive for a BESS?

Q4: Which power plants should be coupled with BESS?

5. Theory and methodologies

This paper is structured by first developing a prediction tool for the SBP power prices using a Seasonal Autoregressive Integrated Moving Average (SARIMA) model. A prediction method for the energy-price is not shown in this paper but references to existing models are provided. Next, a model for energy profits and a model for estimating battery aging are developed. Using all models as inputs, an optimization problem is formulated which generates power and energy bids, maximising revenue and battery lifetime. Lastly, variations of the optimization problem are introduced which are relevant for the determination of a good strategy.

5.1. Seasonal autoregressive integrated moving average (SARIMA) power price model

As explained in chapter II, the auction process for SBP is split up into a power and an energy bid. The submitted power price decides whether the bidding participant gets accepted for a specific product or not. As each bid accepted is considered equal, the critical value to predict is the maximum power price paid per MW acquired (MPPP).

Regarding the time steps that could contain useful information, there are a few which play a role. An intuitive description is given in the following; a statistical proof for that description can be found in Appendix C where relevant autocorrelation function plots are presented.

- **The power price at the same time of the year during the last year(s)**

Seasonal effects such as an increased PV generation in summer have a strong influence on thermal power plant operations and consequently their availability for SBP provision thus changing the supply situation.

- **The power prices during the weeks before the auction analysed**

To grasp the current state of the market, the power prices during the last few weeks should be considered.

A time series model, which includes both above-mentioned factors, is the SARIMA model. The model was chosen for a number of reasons including:

- The SBP market is rather opaque with close to no information revealed about the bids and bidders. This makes a fundamental model of the market challenging and subject to strong assumptions with

Table 1
Description of SARIMA-parameters [17].

Variable	Chosen number of coefficients	Description
p	2	The number of non-seasonal autoregressive coefficients
d	1	The degree of non-seasonal differencing
q	2	The number of non-seasonal moving-average coefficients.
P	0	The number of seasonal autoregressive coefficients
D	0	The degree of seasonal differencing.
Q	1	The number of seasonal moving-average coefficients.

regards to participating technologies and bidding strategies. Developing and tuning such a model was seen as unsuitable for the goals of this paper.

- Neural networks or statistical methods based on external inputs such as fuel prices, wholesale prices, temperature, etc. are in principle possible, but were not feasible in the scope of the project.
- If no other data than the bid results themselves can be used for the reasons given above, a tool in the domain of timeseries analysis is the remaining option. SARIMA is a typically used tool in such circumstances and has successfully been applied to a similar problem before [16]. It combines the frequently used methods of auto-regression, differentiation and averaging. As required by the input time series, the model can handle non-stationary and seasonal behaviour. The choice of method is supported by the evaluation given in Appendix D.

The standard form for writing the different components of a SARIMA model is given in (1). An overview of the chosen number of coefficients and the description of each variable is given in Table 1.

$$SARIMA(p, d, q) \times (P, D, Q)_s \tag{1}$$

The number of coefficients is chosen based on [16] who modelled the Nordic power market using the SARIMA approach. The seasonal components are chosen differently because the dataset only entails 3 years which does not encourage focusing on seasonal effects strongly. It was therefore decided to only use a simple moving-average of the last year. Choosing this parametrisation has been statistically verified both with respect to the initial data series in Appendix C and with the results generated from the model in Appendix D. The weighting factors used were determined using historical market data. Appendix A shows the results of applying the model. The implementation of the SARIMA model used is [17].

5.2. Energy profit model

As explained in chapter II, the SBP revenues depend on both the submitted power bids and energy bids for each product type. The power price related revenues can easily be derived from whether the bidder got accepted or not. However, the revenues based on the submitted energy price depend on the uncertain SBP power demand and the individual position in the merit order. To evaluate the performance of a BESS for a given energy bid, an evaluation algorithm is necessary. This section describes the approach chosen to find the net profit based on the submitted energy price bids.

For the purposes of this paper, the described algorithm uses perfect knowledge regarding the SBP power demand time series and the submitted energy bids of the competitors. In literature, prediction tools have been developed and extensively described, for instance [18–20]. None of these papers however develop a methodology detailed enough to be applied for the purposes of this paper. A prediction tool for both aforementioned components is also out of the scope of this paper and therefore perfect knowledge is used. The results given in this paper thus describe a maximum achievable. This is a typical approach for evaluations of storage devices [21]. Differences between realizable profits and maxima achievable are difficult to quantify, but have been estimated at around 14% [22] and 20% [23]. This corresponds to the authors industry experience where values between 10% and 20% are typically used.

As described in chapter III, the TSOs provide the actual SBP delivery power in a time series with a resolution of 15-minutes. For each quarter-hour, it is determined first whether the quarter-hour is active or inactive. A quarter-hour is active if the BESS has won the power bid auction offering a product during that quarter-hour and consequently an inactive quarter-hour is one in which no product is offered. Both situations require separate responses which are explained in this section.

5.2.1. Active quarter-hour

SBP is called by the TSOs on an instantaneous basis and consequently the power demanded can fluctuate significantly over the course of a quarter-hour. As only averaged 15-minute power values are available, a shape function for the demand had to be derived. The most conservative shape was chosen, namely that the power demanded is the same in both directions and does not vary in magnitude, only in duration for each direction. See Fig. 1 for a visualization of the approach and (2) and (3) for a mathematical description where $P_{pos,av}$ is the average positive SBP demanded during the quarter-hour and $P_{neg,av}$ is the average negative SBP demanded during the quarter-hour. Note that we model the calls as in the middle of 15-min. period if the BESS only offers one product during a given period.

$$P_0 = |P_{pos,av}| + |P_{neg,av}| \tag{2}$$

$$t_{pos} = 15min*\frac{|P_{pos,av}|}{P_0};\ t_{neg} = 15min*\frac{|P_{neg,av}|}{P_0} \tag{3}$$

Based on the above described assumption on the power demand, the actual evaluation algorithm of the quarter-hour can be run. Each quarter-hour is considered separately and one after another. The algorithm first calculates the active duration for each BESS based on the position in the merit-order of energy bids and the power demanded. If the power demanded is greater than the respective position in the merit-order, the BESS is active for that product and must deliver.

The merit order $MO(P)$ is a function of the power required and is created by sorting all accepted bids by their energy bids in €/MWh (EB). The function thus returns a price in €/MWh for any given power P required. The energy delivered as SBP by the BESS for positive SBP (En_+) and negative SBP (En_-) is can be found as follows given the BESS' positive and negative energy bids ($EP_{\text{BESS,pos}}$ and $EP_{\text{BESS,neg}}$ respectively).

$$En_+ = \begin{cases} t_{pos}*P_0 & EP_{\text{BESS,pos}} < MO(P_{pos,av}) \\ 0 & otherwise \end{cases} \tag{4}$$

$$En_- = \begin{cases} -\ t_{neg}*P_0 & EP_{\text{BESS,neg}} < MO(P_{neg,av}) \\ 0 & otherwise \end{cases} \tag{5}$$

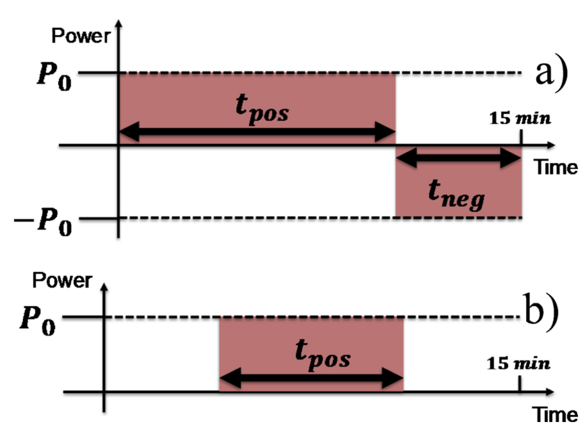

Fig. 1. SBP power provision of a BESS within a quarter-hour block a) positive and negative SBP provision b) positive SBP provision only.

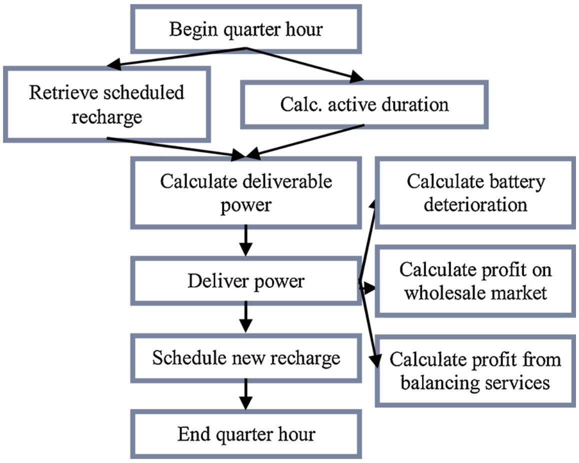

Fig. 2. Schematic of the active quarter-hour profit evaluation algorithm.

Parallel to the SBP delivery, the BESS can recharge energy from the wholesale market or a coupled unit. If for instance the battery is scheduled (e.g. on the wholesale market) to recharge a certain amount of energy and at the same time is called to deliver positive balancing power, the battery can simply reduce the scheduled power by the amount of the SBP requested. If on the other hand a scheduled recharge overlaps with a negative SBP request, the BESS must be able to handle the high overall power. If the BESS buys electricity on the wholesale market to recharge frequently enough, it will always be able to deliver the service it sold even if it is just using its net balance.

When the power is delivered, the battery deterioration and the energy profits or losses due to that delivery are calculated. The default SoC ($SoC_{default}$) is defined as the SoC at which the battery has enough energy reserves for the provision of both positive and negative SBP while fulfilling the 4 h criterion. It is possible that not the full capacity of the battery is marketed e.g. because a negative and a positive bid were placed for the same timeslot, but only one was successful. In this case, the default SoC is defined such that charging cycle depth is minimized. If for instance at least a SoC of 50% is required, but higher would be allowed, then the battery recharges only if it drops below 50%. The algorithm can schedule a recharge on the electricity market for the next period to maximize availability of the BESS and return to default SoC. The full algorithm is given in Fig. 2.

There are two strategies for recharging where the first one is found using (6) and is modelled after the recharge scheme employed for primary balancing power [24]. This scheme is called the "always return to default SoC" scheme. If the BESS operates in conjunction with a power plant, it does not necessarily have to follow that strategy and could remain at another SoC. One approach that realizes this idea is given in (7) where a recharge is only called if the battery would not be able to provide the service marketed for the next 15 min if it did not recharge. The 15 min are somewhat arbitrary but are sufficient time for a power plant to adapt its generation.

$$En_{recharge} = sign(SoC_{default} - SoC)*\min(|SoC_{default} - SoC|*BC, PC_{max}) \tag{6}$$

Where: BC = total battery capacity in MWh PCmax = The maximum energy in MWh which can be recharged due to e.g. battery or converter limitations

$$En_{recharge} = \begin{cases} P_{pos,av}*\frac{1}{4}h & SoC < \frac{(P_{pos,av}*\frac{1}{4}h)}{BC} \\ -P_{neg,av}*\frac{1}{4}h & SoC > \frac{P_{neg,av}*\frac{1}{4}h}{BC} \\ 0 & otherwise \end{cases} \tag{7}$$

The total profits from active quarter hours TP_{active} can be found by multiplying the scheduled energy exchanges with the relevant prices. In vector form, this can be written as:

$$TP_{active} = sum(EP_{BESS,pos}*\vec{En_+}) + sum(EP_{BESS,neg}*\vec{En_-}) + \vec{En_{recharge}}*\vec{MP} \tag{8}$$

5.2.2. Inactive quarter-hour

If the battery is inactive on the SBP market for a given period, it is free to use its capacity for arbitrage trading. The only condition for the inactive period is that the SoC has to return to the default SoC at the end of the period in order to supply the services marketed. The algorithm chosen for arbitrage profit maximization closely resembles and is inspired by the work of [6]. The inactive quarter-hour algorithm iteratively goes through the steps presented in the following:

1 Create a set S_{MP} of the wholesale market prices in all inactive periods.
2 Is $S_{MP} = \{\}$ (i.e. an empty set)? If true, end algorithm.
3 Find the highest market price: $MP_{max} = \max(S_{MP})$
4 For MP_{max}, discharge if possible: $En_{recharge} = \begin{cases} -PC_{max} & SoC_{\text{after discharge}} \geq 0\ \forall\ t \\ 0 & otherwise \end{cases}$ where t is an instance in time.
5 Remove MP_{max} from S_{MP}: $S_{MP} = S_{MP} / \{MP_{max}\}$
6 Find the cheapest period MP_{min}: $MP_{min} = \min(S_{MP})$
7 For MP_{min} charge if possible: $En_{recharge} = \begin{cases} PC_{max} & SoC_{\text{after charge}} \leq BC\ \forall\ t \\ 0 & otherwise \end{cases}$
8 Remove MP_{min} from S_{MP}: $S_{MP} = S_{MP} / \{MP_{min}\}$
9 Go to 2.

The following illustrates the process if the battery has a too high SoC at the end of the arbitrage period SoC_{end}.

1 Create a set S_{end} of the last wholesale market periods with $En_{recharged} > 0$ in the time between the end of arbitrage period and the last time $SoC_{end} = SoC_{end,desired}$.
2 Find the highest market price $MP_{max} = \max(S_{MP})$
3 During MP_{max} set $En_{recharge} = \max(0, PC_{max} - (SoC_{end} - SoC_{end,desired}))$ and recalculate SoC_{end}
4 If $SoC_{end} = SoC_{end,desired}$ then end, otherwise go to 2.

If SoC_{end} is too low, the process is inversed as follows:

1 Create a set S_{end} of the last wholesale market periods with $En_{recharged} < 0$ in the time between the end of arbitrage period and the last time $SoC_{end} = SoC_{end,desired}$.
2 Find the lowest market price $MP_{min} = \min(S_{MP})$
3 During MP_{min} set $En_{recharge} = \min(0, -PC_{max} + (SoC_{end,desired} - SoC_{end}))$ and recalculate SoC_{end}
4 If $SoC_{end} = SoC_{end,desired}$ then end, otherwise go to 2.

The total profits from inactive quarter hours $TP_{inactive}$ can be found by multiplying the scheduled energy exchanges with the market prices at the time. In vector form, this can be written as:

$$TP_{inactive} = \vec{En_{recharge}}*\vec{MP} \tag{9}$$

5.3. Battery model

The battery model used in this paper is based on and closely resembles [25]. The model was chosen since it delivers reasonably accurate results for the loss of life of a battery for individual cycles and because the battery technology, lithium ion manganese oxide, is the same as the largest battery used in M5BAT.

For this paper, the same model parameters are used as suggested by

[25]. Since no specific battery with a cyclic and calendric history was used for the simulation, the fast decay in capacity during the first ˜1000 cycles is not considered and only the linear component of the model between cycle 2000 and 4000 is used. Ignoring the initial fast decay is compensated for by assuming a capacity price of 400€/kWh which is from the upper end of the spectrum for the year 2020 [26]. The price can be understood as a replacement value, i.e. the cost of replacing the spent batteries after reaching their end of life.

The data presented in [25] is based on repeating the same cycle. Providing balancing power however results in an irregular pattern. To overcome this problem, the Rainflow algorithm has been used. It originates from materials science and has been used to analyse the aging of materials in stress-strain tests [27]. It has also been used in battery testing as the problem structure is quite similar [25]. The fundamental idea is that charging and discharging can be counted as half-cycles. Half cycles are counted by their depths and combined to full cycles.

The total costs (i.e. negative total profit) of battery deterioration can be found by multiplying the replacement costs per kWh with the linear capacity lost during operations.

$$TP_{deterioration} = -capacity\ price * capacity\ lost \tag{10}$$

5.4. Bid optimization

When a bidder submits multiple bids, a variety of outcomes is possible. If for instance a bidder has submitted bids in the categories NegHt and NegNt, the possible outcomes are the powerset of these two options as shown in Fig. 3. The usage of the powerset can be generalized for any combination of products offered. For each combination in the powerset, the earnings from providing balancing power, arbitrage and the battery costs are calculated using the scheme introduced in sections V.B and V.C. These earnings are referred to as Energy Earnings (EE) from here onwards and can be obtained as shown in (11).

$$EE = TP_{active} + TP_{inactive} + TP_{deterioration} \tag{11}$$

If a power bid is submitted and accepted, the total revenue for the bidder is the power price (P) plus the EE. The acceptance in turn depends on the height of P as a higher power bid results in a lower likelihood of acceptance. The expected payoff or utility u(P) per combination can then be found by multiplying the likelihood of acceptance for the specific combination $G(P_i)$ with the expected profit as done in (12).

$$u(P_i) = G(P_i)*(P_i + EE_i) \tag{12}$$

$G(P_i)$ is the probability of acceptance of the specific combination which can be found by following the branches of Fig. 3. The probability of a certain outcome at each branch can be found using the SARIMA prediction method introduced in section V.A. Since the model provides an expected mean and a standard deviation, the cumulative distribution function (CDF) of the normal distribution can be used for $G(P_i)$. If (12) is applied on all combinations of possible outcomes and then the results summed up, the total expected profit or utility U can be found as follows:

$$U = \sum^{i} G(P_i)*(P_i + EE_i) \tag{13}$$

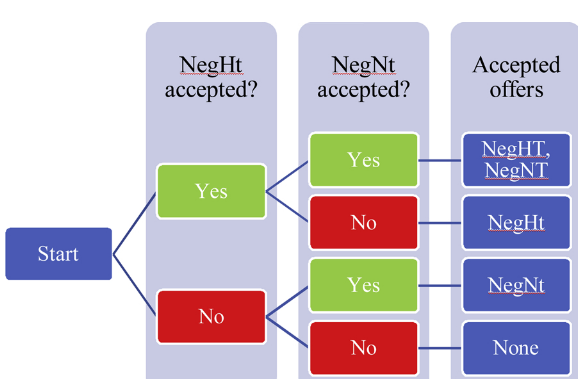

Fig. 3. Example of potential outcomes if a bidder submits two bids.

The optimization problem was solved using a Covariance Matrix Adaption Evolutionary Strategy (CMA-ES) Optimizer. CMA-ES is a flexible yet robust algorithm to optimize black box problems. It has been developed and implemented by Nikolaus Hansen and has since been incorporated into the Java apache commons math package.

5.5. BESS properties

There are various configuration options for BESS and possibilities in the operating strategy that have an impact on the revenue and the behaviour on the SBP market. These options serve as input parameters to the optimizer. It is important to realize that some properties are only available if the BESS is pooled with a power plant. In the pooled operation, the TSO will regard the BESS and the power plant as one device. This allows for various synergies between the technologies. The characteristics only available in pooled mode are:

- Fixed recharge price

If the BESS is connected to a power plant, all charge operations are modelled as a consumption of energy generated in the power plant and discharging as a reduction of the power plant's generation. The value of the recharged electricity can thus be approximated by the variable costs of the connected power plant. See Appendix B for an overview of the prices used.

- Power/Energy Ratio

In coupled operation with a power plant, the battery does not have to comply with the 4-hour criterion as the power plant can serve as a backup if the battery runs out of energy. This allows for a higher Power/Energy ratio which is beneficial for many common battery technologies including lithium ion [28]. The two chosen options are 0.25 MW/MWh and 1 MW/MWh. A simplification is made by assuming that the connected power plant does have the capacity to spare. As batteries buffer the irregular pattern of balancing power into a much more regular pattern with significantly lower amplitude, it is realistic that a power plant keeps such a tiny fraction of power available.

- Recharging Strategy

If the battery has a power plant as a backup with a sufficiently large fuel supply, the battery does not necessarily have to return to the default SoC. The two options are explained in section V.B.1).

In addition, there are two more properties which have been analysed in detail:

- Limited Energy Price

A high energy price could earn the weekly revenue in a few critical minutes. This reduces battery cycling and aging, but increases the risk of not being called at all and thus not generating any revenue. The two options are unlimited energy prices and prices limited to three times the average energy price of the week.

- Offered products

A BESS can offer any of the four SBP products to the market or a combination thereof. For this paper, all calculations were performed on

Table 2
Independent properties for BESS to be set before optimization.

Properties	Options
Connected Power Plant	None, Biofuel, Geothermal, Bituminous Coal, Lignite, Lignite with Carbon Capture and Storage (CCS), and Natural Gas
Limited Energy Price	Not limited, 3x mean energy price
Power/Energy Ratio	0.25, 1
Recharging Strategy	Return to default SoC, Reduce number of cycles
Offered Products	NegNt, NegHt, PosNt, PosNt

a per MW basis and the optimizer was free to allocate the capacity to any of the offered products as long as the overall battery power capability of 1 MW was not violated.

An overview of all properties and the available options is given in Table 2.

6. Results

6.1. Dependency analysis

This section reports the results obtained when comparing the various dependencies described in Table 2. The sub research questions Q1 – Q4 are directly answered in this section thus answering the overarching combined question *Q*.

6.1.1. Strategy properties' influence on profit

In order to analyse the impact of the strategy properties on the total profit obtained, a linear model was trained on the result data to give approximate weights to each component of a strategy. Both weights and p-Values for each weight are produced where the p-Value indicates whether the linear model could accurately evaluate the impact of a certain strategy. The model starts at an offset of -425.46 €/week and the mean expected profit for a strategy can be found by linearly combining the available options explained in section V.E with the impacts given in the following. The results were found using MATLAB's fitlm function.

- Limiting the energy bid to 3x the week's mean energy limit price results on average in a surplus of 257.48 €/week
- Not returning to the default SoC increases average profits by 47.21 €/week
- Increasing the power to energy ratio to 1 MW/MWh raises average profits by 699.79 €/week.
- If the following products are offered, the weekly earnings increase by
  - ○ NegHt: 70.83 €/week
  - ○ NegNt: 419.75 €/week
  - ○ PosHt: 147.14 €/week
  - ○ PosNt: 280.70 €/week

For all above results, the p-value of the fitlm is near 0 indicating that a linear model is a reasonable approach. The effect of being connected to different power plants as well as the corresponding p-value for each combination is given in Table 3. The R2-value for the model is 0.29 for the 131,374 observations made.

From the list and table above, all research sub-questions *Q1 – Q4* can answered with answers *A1 – A4*. *Q1* and *Q2* are also discussed further in the discussion and conclusion chapter VII.

A1: The maximum possible revenue of a BESS on the SBP given perfect energy foresight is 1881 €/week which can be found summing up all options (i.e. all values in the list above) and combining it with a geothermal power plant.

A2: The power to energy ratio is the most economically impactful aspect of operating a BESS on the SBP market as profits change most significantly out of all available options.

Table 3
Average contribution from being connected to the power plants. Standalone application serves as base scenario.

Connected Power Plant	Contribution in €	p-value
Biofuel	−21.25	0
Bituminous coal	−3.01	0.02
Natural gas	−20.44	0.92
Geothermal	383.46	0
Lignite	−17.70	0.64
Lignite with CCS	−15.31	0.44
Standalone application	0	0.01

A3: NetNt is the most attractive SBP product for a BESS as it provides the highest profits on average.

A4: The BESS should be coupled with an expensive power plant such as a geothermal power plant.

6.1.2. Relationships per product

For each product, there are two relationships of interest, namely the relationship between the type of power plant connected and the power offered, or profits made. The optimizer will offer more power if the connection to a power plant is more profitable. Understanding these relationships consequently shows what constellation of BESS and power plant requires which strategy and shines additional light on *Q3* and *Q4* (Tables 4 and 5).

6.2. Performance indicators

Since this paper uses of a numerical optimizer, convergence must be checked. The achieved convergence rate was mostly in the range of 92%–97% for each week and never lower than 85%. To determine whether any strategy property had a strong impact on the convergence and might therefore cause an inaccuracy in the overall result, the fraction of bids submitted with a certain strategy property was

Table 4
Contribution of power plant to power offered per product. Example on how to read the table: A participant offering NegNt with a biomass plant connected used on average 76.54% of its available power for the service.

Connected Power Plant	Power offered as % of available power			
	NegNt	NegHt	PosNt	PosHt
Biomass	76.54	72.31	51.27	54.03
Bituminous coal	67.19	63.53	65.29	67.20
Natural gas	76.11	72.20	51.47	54.50
Geothermal	85.26	82.39	32.75	35.15
Lignite	75.75	71.40	52.22	55.62
Lignite with CCS	77.16	72.98	50.13	52.64
Standalone application	64.51	64.68	68.13	66.26

Table 5
Contribution of power plant to profit per product. Example on how to read the table: A player offering NegNt with a biomass plant connected earned on average 1046 €/week.

Connected Power Plant	Average profit in € for product with power plant			
	NegNt	NegHt	PosNt	PosHt
Biomass	1046.30	431.85	426.40	237.64
Bituminous coal	709.53	321.77	645.55	327.12
Natural gas	1051.44	433.86	431.73	240.84
Geothermal	2094.37	1202.77	171.64	112.26
Lignite	1001.06	409.75	456.16	251.68
Lignite with CCS	1090.18	450.04	404.88	227.60
Standalone application	718.99	362.91	680.86	315.33

Table 6
Average bid, offer rate, and acceptance rate of all converging bidders.

Parameter	Value for product			
	NegNt	NegHt	PosNt	PosHt
Average bid	91.22%	87.77%	85.39%	80.55%
Offer rate	74.66%	71.38%	52.97%	55.01%
Acceptance rate	47.69%	19.87%	89.97%	93.37%

compared to the fraction expected if all bids converged. The maximum derivation across all properties was 1.62% for the optimizer strategy which is an acceptably low value and no systematic influence on results could be found.

As part of the optimization, the algorithm decides how much of the power available is offered. The acceptance rate of the bids made on the other hand indicates the risk the algorithm is willing to take. Understanding these dependencies can give an indication of what offers are attractive and how the structure looks like. Their description is given in the following. Table 6 shows the results for the simulation run.

- Average bid

The average bid is the measure of the average power bid by all bidders excluding offers of 0 MW as these are not considered a valid offer.

$$Average\ bid = mean(PB_i)\ \ \forall\ PB_i \neq 0$$

Where PB_i is the power bid submitted by bidder i.

- Offer rate

The offer rate is defined as the power offered by all bidders divided by the power that could have been offered for that product by all bidders. It differs from the average bid by the fact that the offer rate does consider offers of 0 MW whereas these are ignored in the average bid.

$$Offer\ rate = \frac{\sum_{i=1}^{n} \frac{PB_i}{PB_{max,i}}}{n}\ \ \forall\ PB_i$$

Where n is the total number of bids submitted and $PB_{max,i}$ is the maximum power bid that bidder i can submit.

- Acceptance rate

The acceptance rate is the total power accepted per product divided by the total power offered for said product.

$$Acceptance\ rate = \frac{\sum_{j=1}^{k} \frac{PB_j}{PB_{max,j}}}{n}$$

Where k is the number of power bids that were successful in the auction and PB_j is the j' ths bid in the collection of the successful power bids.

7. Discussion and conclusion

From the results presented in chapter VI, several interesting observations can be made and several rules for what defines a good strategy can be distilled. This chapter summarizes and discusses some of the main results.

7.1. Winning strategy

From the dependency analysis, we can derive which factors determine a good strategy for a BESS on the SBP market and thereby dive further into *Q1* and *Q2*. The main conclusion to be drawn is that while it is difficult to imagine BESS becoming profitable on the SBP in standalone operation, there exist numerous ways in which they could be if combined with a pool of other power plants. The combination with a power plant allows the battery to break the 4-hour criterion meaning that it can offer more power per unit of energy stored. Considering various combinations of strategy properties, the following conclusion can be drawn:

> The most successful strategy is one of a BESS with a high power to energy ratio, connected to a geothermal power plant, that limits its energy bids and does not return to the default SoC. The BESS should consider offering all products

This combination reaches a mean profit of €1881 per week. While this number seems high, one must keep simplifying assumption in mind such as perfect foresight and the fact that the extremely expensive generation of a geothermal power plant was replaced. For more realistic scenarios, profits in the order of €1000 per week can be achieved in combination with a power plant and around €300 per week for standalone applications.

Some choices are surprising at first and a more detailed analysis of the dependencies shows some background structure of the result found. This is done in the following sections.

7.1.1. Power plant and offered products

In our analysis, the most expensive power plant allows for the highest profits. The geothermal power plant enhances the profits of the negative products significantly because the electricity absorbed in the balancing process replaces the own generation. While a very expensive plant is unlikely to actually operate, it can be concluded that providing negative balancing power can be a replacement of power generation if the alternatives are expensive. Similarly, it was shown that for plants with low variable costs, such as lignite power plants, it is attractive to be combined with a battery as they are then able to increase their sales on the balancing power market using the battery as a buffer.

7.1.2. Recharging strategy and power to energy ratio

It was found that not returning to the default state of charge had a positive impact on the total profit since it decreased the amount of cycles the battery had to go through. The impact is however relatively insignificant compared to other factors and could be disregarded. In turn, this means that the recharging strategy is not the deciding argument for the battery operation in a pool.

Increasing the power to energy ratio on the other hand is very successful and generates significantly higher profits. This can be explained by the fact that a battery naturally has a higher power/energy ratio than 1 MW/4 MW h. If the battery must limit its power output, it wastes some of its potential. Altering this criterion to a more suitable power/energy ratio of 1 MW/1 MW h allows for the battery to use its full potential.

The profits displayed could be combined with alternative sources of revenue. If located on the site of a large power consumer, the battery could be used to reduce peak energy consumption thus lowering grid fees or if the inverter is capable enough to provide reactive power thus replacing an otherwise potentially expensive compensator. Depending on the regulatory regime, a BESS may also serve in an uninterruptable power supply system. All these potential benefits are however beyond the scope of this paper.

In this project, the wholesale market was regarded mainly as a mean to bring the SoC back to normal, but joint optimization of SBP bids and arbitrage trading would possibly also yield some gains. Doing so could be subject to follow-up research. Initial results from battery deterioration results make the author however sceptical as to whether BESS should strongly focus on arbitrage trading.

7.2. Standalone operation

As seen in section VI.A, the connected power plant has a significant impact on the performance of the battery. If the results for the battery in standalone application are analysed, one can see right away that the profits obtainable drop significantly to no more than about 300–500 euros per MW per week. With primary balancing power, a battery could earn €2500 – €3000 per MW [7] in 2015, but prices have since dropped further to about €1600 – €2000, which is still a multitude of what has been calculated in standalone. Consequently, a battery is unlikely to operate as a standalone unit on the SBP market.

7.3. Limitations

The results of this paper have several limitations which will be listed in the following.

- Modelling of pool operation

The value of a battery in a pool depends significantly on the constellation of the pool. To properly evaluate the value of the battery, the precise constellation and operating condition of a pool must be known. As this is outside the scope of this work, the pool operation was simplified. Modelling the full pool would result in a more accurate estimate of the profitability of a battery in a pool.

- Limited battery model

The battery model considered for this paper was chosen because of its simplicity resulting in low calculation times. Factors such as self-discharge, inefficiencies in inverters and transformers, or the non-linearity were ignored. One especially problematic factor is the modelling of battery aging depending on the SoC over time as it is only parametrized for relatively high SoCs of 60% and higher. For low SoCs, the predicted loss of battery life reduces significantly. Tests carried out with similar cells indicate that this confirms with reality [29], but a proper confirmation is missing.

- Prediction models

For this paper, no prediction model for the energy price and corresponding request frequencies was used and instead replaced by perfect foresight.

Further, the SARIMA algorithm is solely a timeline analysis ignoring other potentially important input factors such as vacation times or bank holidays. Further the prediction for positive products experiences a conditional heteroscedasticity. To overcome this issue, a GARCH-SARIMA model instead of a simple SARIMA model could to be used.

Acknowledgements

The project upon which this publication is based is funded by the Federal Ministry for Economic Affairs and Energy under project number 03ESP265A (M5bat). The authors of this publication are responsible for its content.

Appendix A. SARIMA Prediction Performance

This section contains the graphs showing the prediction accuracy of the SARIMA models. The red line is the historical MPPP for a MW of power per week. The background in yellow and blue indicates the predicted likelihood of the maximum price being that value where yellow means high likelihood and blue low likelihood. The prediction is made using historical data only by applying the SARIMA analysis to the previous week and a good match is achieved. Due to some strong fluctuations in the series, the standard error however is also quite large as can be seen in Table A1.

See Figs. A1–A4.

Table A1
Standard errors of SARIMA predictions.

Predicted Product	NegNt	NegHt	PosNt	PosHt
Standard error of forecast in €	172.24	158.03	104.76	54.61

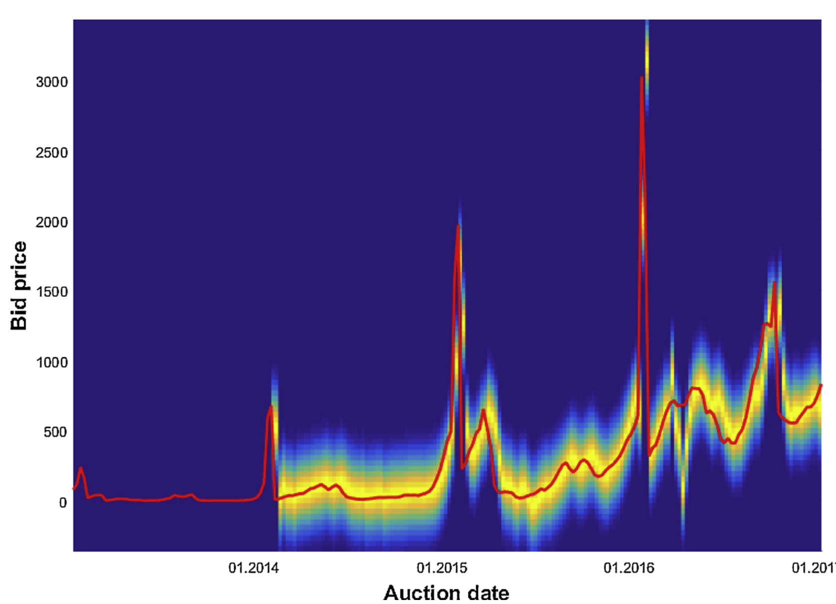

Fig. A1. Comparison of SARIMA prediction and historical MPPP for NegHt.

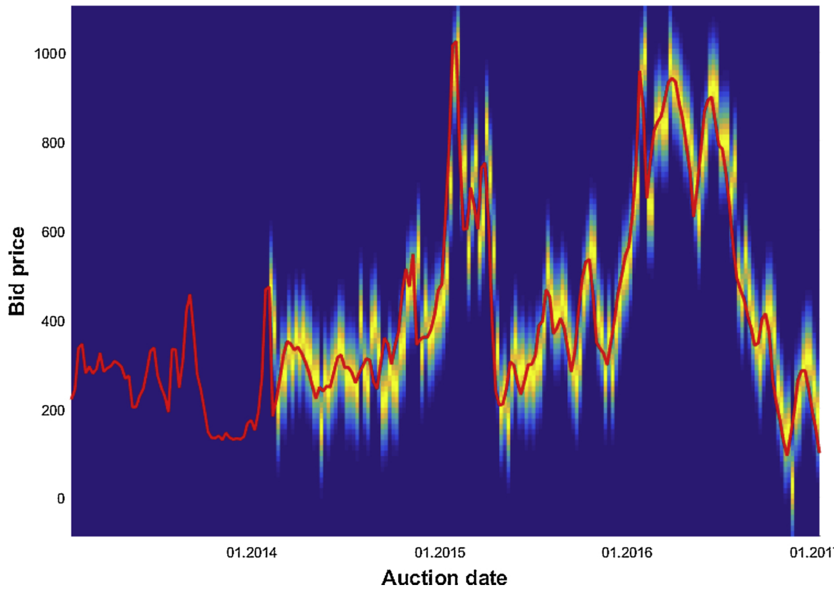

Fig. A2. Comparison of SARIMA prediction and historical MPPP for PosHt.

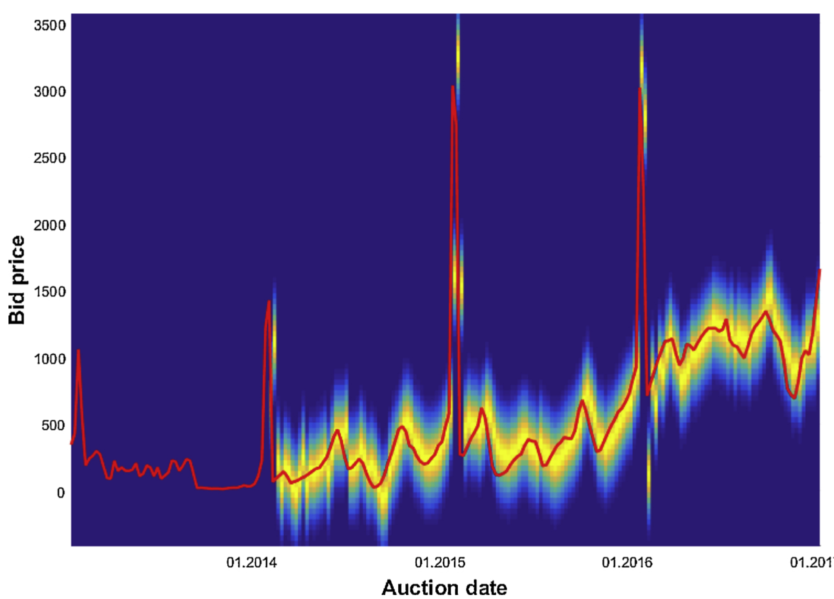

Fig. A3. Comparison of SARIMA prediction and historical MPPP for NegNt.

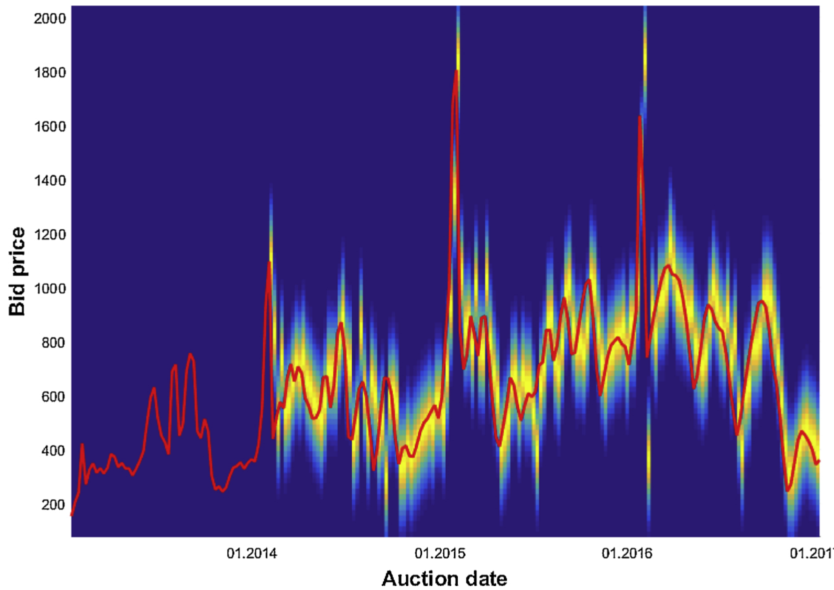

Fig. A4. Comparison of SARIMA prediction and historical MPPP for PosNt.

Appendix B. Costs of Power Plants

See Table B1.

Table B1
Fuel costs for different types of power plants [30].

Plant type	Fuel Costs [€/MWh]	CO_2-emissions [tCO_2/MWh]	Total costs [€/MWh]
Geothermal	250	0	250
Lignite with CCS	80.49	33	80.65
Biofuel	75	0	75
Natural gas	71.74	202	72.75
Lignite	66	410	68.05
Bituminous Coal	32	342	33.71

See Fig. B1.

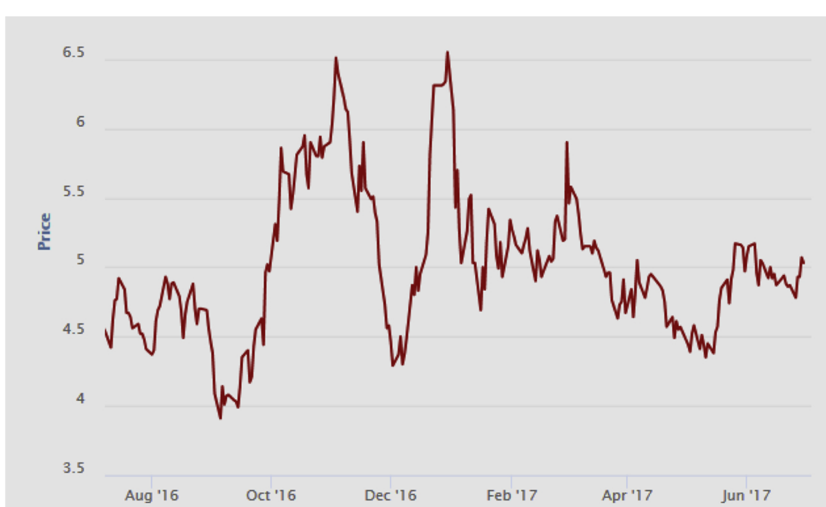

Fig. B1. Price for European CO2 emission allowances [31].

Appendix C. Determining the Necessary Size of a SARIMA Model

This section contains several plots which show how the minimum parameter size of the SARIMA model can be derived.

First, the data was checked for stationarity using the augmented Dickey-Fuller test. NegNt, NegHt, and PosNt have a low p-value below 0.05 indicating that no stationary trend exists. This means that for these products a SARMA model would have been sufficient. Because of the stationarity, the integrating component of the model does not have any function as it is meant to compensate for a deterministic trend. Only the maximum prices paid for PosHt experience a deterministic trend with a p-value of 0.190. For this curve, it was consequently necessary to include the integrating component. If the same test is applied after differencing the time series once, it can be tested whether the trend is deterministic. The resulting p-value was $2.2*10^{-16}$, so almost zero. This indicates that integrating once is sufficient and consequently a linear differencing suffices. The same set of parameters is used for all 4 products to compensate for any trend which might arise in future simulations.

See Table C1.

Table C1
p-value for the augmented Dickey-Fuller Test checking for stationarity.

Timeseries	p-value
NegNt	0.034
NegHt	0.008
PosNt	0.003
PosHt	0.190

Autocorrelation Function

Fig. C1 shows the autocorrelation of the time series of the highest power price paid each week for each product. The blue dotted line indicates an autocorrelation within the 95% interval of confidence. Note that the first bar indicates the lag 0 and is therefore irrelevant for this analysis

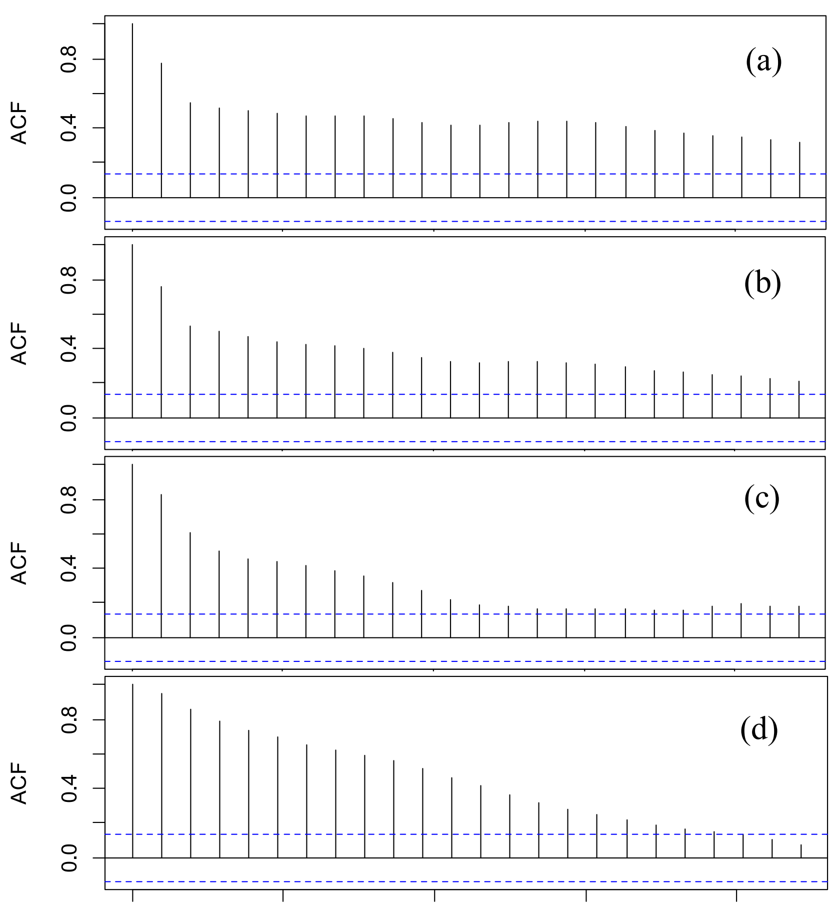

Fig. C1. Autocorrelation function of time series of MPPP for NegNt (a), NegHt (b), PosNt (c), PosHt (d) with the lags on the x-axis.

Autocorrelation of First Difference

To truly test which lag is significant, one can produce the same kind of plots of the first difference which was done in Fig. C2. If the predictive model contains an integrating component, we are only interested in checking how many significant lags there are after differencing. It can be seen that the number of significant lags is reduced to 2 or 3. As the significance of the third lag is just above the threshold level, it was decided to discard that lag for the sake of a simpler model.

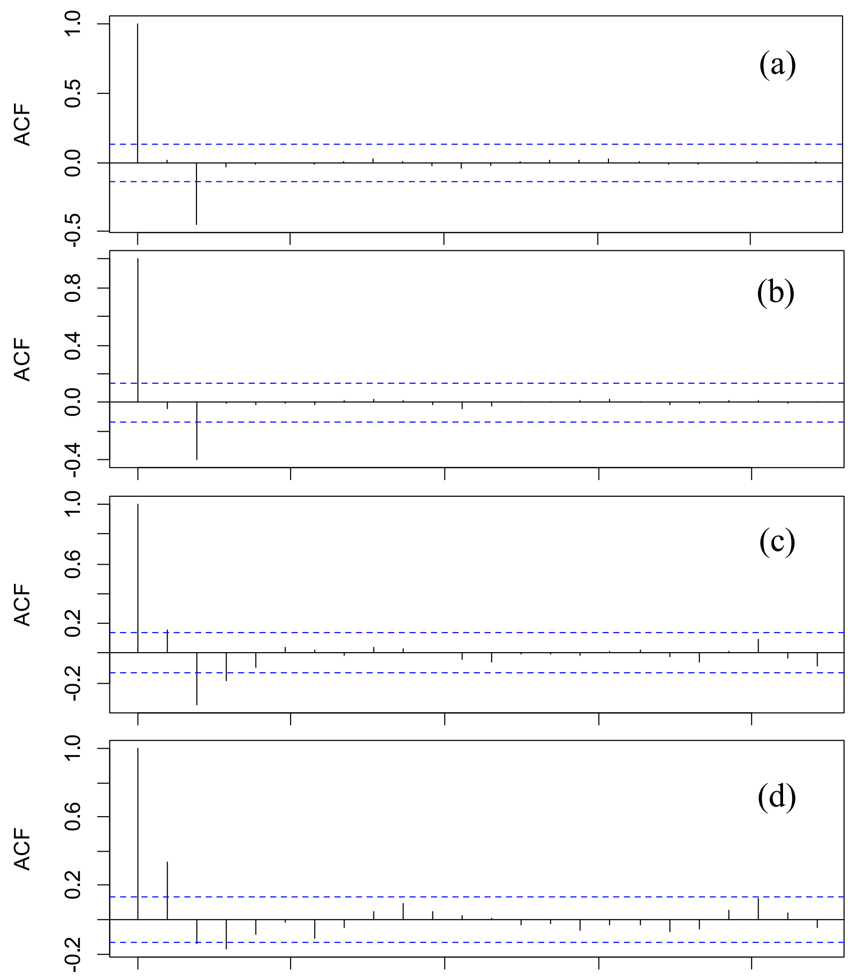

Fig. C2. Autocorrelation function of the first difference of time series of MPPP for NegNt (a), NegHt (b), PosNt (c), and PosHt (d) with the lags on the x-axis.

Partial autocorrelation function

The partial autocorrelation function provides information about the number of autocorrelative lags that need to be considers for AR models and all models derived from them such as the SARIMA model. Fig. C3(a) shows 6 significant lags, Fig. C3(b) and (c) shows 4 significant lags, and Fig. C3(d) shows only 2 significant lags. Based on this observation, the amount of AR lags for all models would have to be chosen as 6. As the 6th and 4th lags are just above the threshold level for all three plots it is acceptable to only use the second lag

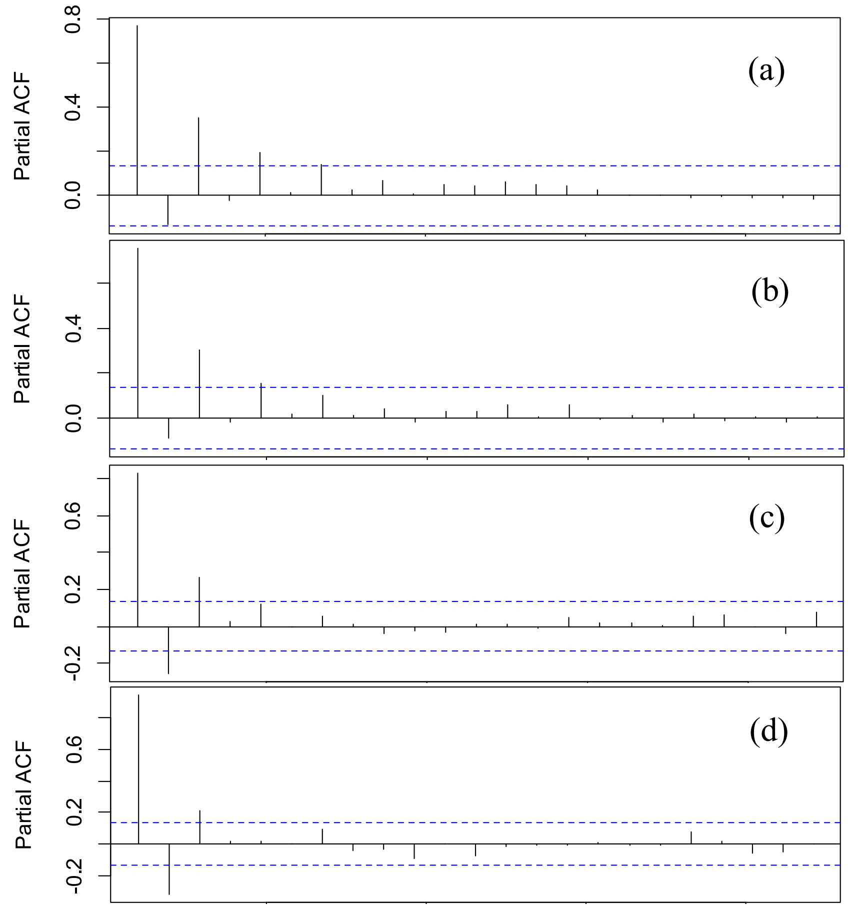

Fig. C3. Partial autocorrelation function of time series of MPPP for NegNt (a), NegHt (b), PosNt (c), and PosHt (d).

Appendix D. Evaluation of SARIMA prediction

This section contains some evaluation parameters of the SARIMA prediction. It was checked whether the residuals still have a significant correlation to previous lags. If such a correlation is found, it is a proof that the SARIMA model is incomplete.

Autocorrelation of residuals

Analysing the autocorrelation of residuals provides information about whether the mean value predicted by the SARIMA model is correct. Table D1 shows the results of applying the Ljung-Box test on the residuals of the prediction. A high p-value near 1 indicates that there is no significant autocorrelation of the error terms with any previous values. As can be seen, all p-values are extremely close to 1, so the means predicted are valid and no further information could have been extracted from the timeseries.

Table D1
Box-Ljung test performed on residuals of SARIMA prediction.

SARIMA prediction of product	p-value of Ljung-Box test
NegNt	1.0000
NegHt	0.9968
PosNt	1.0000
PosHt	0.9995

Conditional Heteroscedasticity

Conditional heteroscedasticity occurs if the variability (i.e. standard deviation) is not equal across the predicted values but depends on the sizes of the previous error terms. For the concrete example of the SARIMA models used, it means that the mean predicted is correct, but the standard deviation is not always correct across the range of predicted values. An example of such a situation is if the standard deviation increases with increasing mean value which a SARIMA model is not able to capture as it assumes a constant standard deviation across the entire predicted set. Table D2 shows the result of applying the Ljung-Box test on the squared residuals for the timeseries of the MPPP per week for all products. A p-value near 1 indicates that no conditional heteroscedasticity exists and a low p-value the opposite. For the negative products, the p-value is satisfying, but not for the positive products. To overcome this problem, the model would have to be extended with a generalized autoregressive conditional

Table D2
Results of performing the Ljung-Box test on the squared residuals of the SARIMA models' predictions.

Product tested	p-value of Ljung-Box test on squared residuals
NegNt	0.9996
NegHt	0.9843
PosNt	0.02878
PosHt	0.00090

heteroscedasticity model (GARCH model). Since the problem is only related to the standard deviation of two of the four products, it was decided to allow this mistake in the model for the sake of calculation speed and simplicity.

Appendix E. Simplifying Assumptions

For the readers convenience, this section lists all simplifying assumptions made through this paper and references the explanatory section in the document.

- Perfect foresight/knowledge is used for the balancing energy demand (see section V.B)
- Arbitrage optimization for periods without any balancing product offered is done without consideration for losses (see section V.B.2)
- Battery deterioration is calculated using only linear components (see section V.C)
- Balancing power demand is calculated using simplified blocks from the 15-minute averages (see section V.B.1)
- If a battery is connected to a power plant, it can always recharge through that plant (see section V.E)
- Power plants are able to supply balancing energy in emergencies thus circumventing the 4-hour criterion (see section V.E)
- The behaviour of the BESS does not influence other suppliers as historic market data is used (see section III)

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