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# Use of battery storage systems for price arbitrage operations in the 15- and 60-min German intraday markets

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ABSTRACT

Over the last few years, electrical storage and especially battery systems have seen a strong rise in interest. In several countries, as for instance in Germany, lithium-ion batteries are now commonly deployed in end-consumer installations to shift local generation from photovoltaic systems in time. A further application for storage is price arbitrage, which corresponds to an operation strategy benefitting from price differentials. In this work, we describe a Mixed Integer Problem to optimize the storage dispatch considering both the 15- and the 60-min auctions in use in Germany. Furthermore, in addition to the calendric lifetime, the limitation to a certain number of cycles is considered in the evaluation. Last, it was conducted a sensitivity analysis to identify the price volatility level that is required to generate a profit from arbitrage operations. Therefore, a market price process with adjustable parameters has been implemented.


## 1. Introduction

As the share of renewable, non-dispatchable and intermittent generation is continuously growing, its integration in power systems becomes increasingly challenging. Apart from further increases in demand flexibility and additional investments in grid infrastructures to enable the integration of renewable generation, storage systems are considered as a potential solution. A recent classification for the usage of storage systems is provided in Refs. [1–3]. One of the most prominent applications is arbitrage, which describes an operation strategy where an agent aims at benefiting from price differentials by buying energy at a low price and selling it at a higher price. It can be implemented on a spatial and/or temporal scale. Spatial price differences occur between two different markets, when prices for a particular time period are lower in one market than in the other market. In that case, one can profit by purchasing at the market with the lower price and simultaneously selling at the higher price market. As the traded energy is not transferred in time, but only between different markets, no storage is required. Inter-temporal arbitrage refers to shifting energy in time and hence requires storage. In this case, energy is purchased, stored for a temporary time-span, and sold back to the market at a later point in time. The profit of the agent is determined by the revenues from selling energy (by discharging the storage device) minus the purchasing cost (to charge the storage device). Furthermore, efficiency losses and the capital cost of the storage system have to be considered in order to conduct a proper economic evaluation.

The existing literature widely recognizes that arbitrage operations did not break-even in the recent past. Steffen [4] analyzed the prospects of pumped hydro storage installations in Germany looking at the years 2002–2010 and found that revenues showed a high volatility and declined over the last few years. He concluded that the expected profit from arbitrage operations is not sufficient to justify a commitment by a typical utility. Kloess [5] analyzed arbitrage profits in the Austrian market from 2007 to 2011 and found a decline of revenues of about 60% over the time horizon. Zakeri and Syri [6] conducted a similar analysis in the Nordic market from 2009 to 2013 and concluded that arbitrage revenues are very volatile and not sufficient to break-even. Barbour et al. [7] identified a similar variability of returns in the UK market as well as a decrease in annual revenues of 75% along two years. Woo et al. [8] compared the revenues across several markets for the years 2005–2009. In line with the previous authors, they found high variations, both between markets as well as among individual years. Looking at historical data from 2007 to 2011 for the Nord Pool, EEX, UK, the Spanish and the Greek markets, Zafirakis et al. [9] determined that arbitrage revenues vary widely between markets and are not sufficient to justify storage investments. McConnell et al. [10] looked at the Australian market over the years 2004–2014. Even though they did not take investment cost into account, a strong decrease in revenues was obvious. Bradbury et al. [11] considered seven U.S.

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markets and investigated the year 2008 as it exhibited high price volatility. Nonetheless, most technologies they compared would not have been able to break even.

Overall, in the recent past arbitrage was not able to deliver sufficient returns in any of these markets to justify a storage investment. However, several market places have experienced important structural changes over the last few years for instance related with the wide spread occurrence of negative electricity prices. Furthermore, in the German market, a 15-min auction was introduced in addition to the existing 60-min auction. These auctions introduce extra flexibility mechanisms allowing agents to adjust their positions. The experience since 2011 shows that these are important instruments in a system highly driven by renewables and that the volumes traded on the 15-min auctions are strongly correlated with the intermittence of solar generation.

Both factors are likely to increase the arbitrage opportunities and therefore the theoretical revenue potential. However, negative prices might lead to unpredicted outcomes in storage dispatch models. After fully charging the storage device, simultaneous charge- and discharge operations – which are not feasible from a technical perspective – are the economic optimal solution once the storage device is fully charged due to the occurring efficiency losses and resulting monetary gains. In existing evaluation models, this situation is oftentimes not yet considered.

Furthermore, the participation in a second simultaneous market is usually difficult to be integrated in existing models thus justifying the development of new models as well as the re-evaluation of the results previously reported on this issue.

Apart from changes on the market framework, the available storage technologies also experienced important developments in recent years. Driven by significant investment cost reductions and technological advances, lithium-ion battery storage systems experienced a strong rise in interest, with several installations already deployed for the provision of primary reserve control. Contrary to pumped-hydro systems, which have been widely analyzed in the past, the lifetime of battery systems is typically not only limited by a calendric lifetime limit, but also by an operational lifetime limit. While some papers recognize the need to include the degradation resulting from storage operations (e.g. [12,3]), this effect has only recently been internalized in evaluation models. As an example, Shang and Sun [13] studied the installation of batteries in electric vehicles and found that when considering degradation, revenues from arbitrage operations are no longer sufficient to overcome implicit cost. Wankmüller et al. [14] suggest that storage systems deployed for arbitrage purposes should pursue only the most profitable opportunities to increase the net present value. Given the high relevance and the significant impact on the financial evaluation, the dual limitation by the calendric as well as the operational lifetime should therefore be incorporated in the models.

In this work, the previously mentioned shortcomings of existing research are addressed. Accordingly, the paper describes an optimization framework to identify the profit maximizing dispatch, admitting the occurrence of negative prices, the existence of two parallel markets – the 15- and the 60-min auctions as already in operation in Germany – as well as the dual lifetime limitation. In addition, an approach is described and applied to estimate the price volatility level that is required for storage devices to break-even.

## 2. Dispatch model

### 2.1. Mixed integer formulation

In order to determine the optimum dispatch of the storage device, a Mixed Integer Problem (MIP) was developed. The simulation is performed in discrete time steps. Index $t$ refers to the individual simulation time steps and $T$ to the time horizon of the simulation. The duration of each time step $\Delta t$ is expressed as fraction of an hour and set to 0.25, as we will be considering 15-min intervals. Power flows are assumed to be constant during each time step and no ramping rates or response times are considered. Table 1 summarizes the relevant simulation parameters and variables.

**Table 1**
Simulation parameters and variables.

| | | |
|---|---|---|
| $t$, $T$, $\Delta t$ | [-, -, h] | Index, simulation horizon and duration of each time step |
| $E_{Storage}(t)$ | [Wh] | Current charge of the storage device |
| $P^{In}_{Storage}(t)$,$P^{Out}_{Storage}(t)$ | [W] | Power absorbed/supplied by the electric storage device |
| $P_{15}(t)$, $P_{60}(t)$ | [W] | Participation in the 15-/60-min auction and resulting power exchange with the grid |
| $P^{Limit}_{15}$,$P^{Limit}_{60}$ | [W] | Power limit for the participation in the 15-/60-min auction |
| $R_{15}(t)$, $R_{60}(t)$ | [EUR/Wh] | Market price of the 15-/60-min auction |
| $Hurdle$ | [EUR/Wh] | Hurdle rate |
| $\eta^{In}_{Storage}$, $\eta^{Out}_{Storage}$ | [%] | Charge/discharge efficiency |
| $E^{Capacity}_{Storage}$ | [Wh] | Rated energy capacity of the storage device |
| $P^{Capacity}_{Storage}$ | [W] | Rated power capacity of the storage device |
| $\delta_{Storage}$ | [%] | Maximum depth of discharge |
| $b_1(t)$, $b_2(t)$, $y(t)$ | – | Binary variables |

The power flows of the storage device are represented by $P^{In}_{Storage}(t)$ and $P^{Out}_{Storage}(t)$. The former represents charging power flows and can only assume negative numbers. Discharging power flows are represented by the latter and can only assume positive numbers. The objective of the storage agent is the maximization of his gross profit, that is the revenues obtained from the energy injected in the grid minus the cost of buying the energy taken from the grid. Therefore, the power flows for the charging and discharging operations are weighted by the current market prices. To consider the simultaneous participation in the 15- and in the 60-min auctions, the associated variables are differentiated by the subscript $_{15}$ and $_{60}$. A positive value for $P_{15}(t)$ or $P_{60}(t)$ represents power taken from the grid during the time period $t$ in the 15-min/60-min market, whereas negative values indicate power injected in the grid. The market prices for each time period $t$ is $R_{15}(t)$ for the 15-min auction and $R_{60}(t)$ for the 60-min auction. For our analysis, we will assume perfect knowledge of future prices. In addition, we assume that market agents act as price takers, hence a market participation does not cause any feedback reaction on the market price. As each transaction covers only a short time horizon, the time value of money is not considered in this dispatch problem. Furthermore, additional operational costs besides the immediate energy cost are not considered. While these are important issues to consider in an implementation, they would further complicate the analysis and are therefore not considered in this document.

However, as even small price differentials would be exploited under the described objective and the assumption of no operating cost, this dispatch could result in a very large number of operations. This might be undesirable due to a premature wear-down of system components as well as further transaction costs. The problem becomes more complex for storage technologies such as batteries, whose lifetime is typically limited both by a limited amount of energy throughput during their lifetime as well as calendric aging. If the storage device is dispatched very frequently, it will soon be at the end of its operational lifetime not profiting from attractive arbitrage opportunities during the remaining theoretical calendric lifetime. On the other hand, if the storage device is dispatched too restrictively, its calendric aging will be the determining factor and not sufficient arbitrage opportunities will be pursued. Therefore, an additional term ("hurdle") is included in the objective function for each storage discharge operation. This factor represents a revenue threshold, such that the storage device is only dispatched if the gross profit from this operation exceeds a prespecified margin. Its integration ensures that only those opportunities are pursued which are sufficiently profitable, as otherwise this term would become negative and hence this charge-/discharge-operation would not be considered. The determination of an appropriate hurdle rate will be discussed in Section 2.3. The objective function is then given by Eq. (1).

$$\max \Delta t \times \sum_{t=1}^{T} \left(-P_{15}(t) \times R_{15}(t) - P_{60}(t) \times R_{60}(t) - hurdle \times P^{Out}_{Storage}(t)\right) \quad (1)$$

The problem is restricted by a range of constraints. The power flow in the 60-min auction must be constant during the complete hour. However, as the simulation interval is only 15-min, Eq. (2) ensures that the power is constant during every 15-min intervals of each hour. In order to account for charging- and discharging efficiencies, the power flows with the storage device are split into $P^{In}_{Storage}(t)$ (charging) and $P^{Out}_{Storage}(t)$ (discharging). Eq. (3) then ensures that the power flows are balanced, hence that the power exchange with the grid equals the charge/discharge power flow.

$$-P_{60}(t-1) + P_{60}(t) = 0 \; for \; t = 2, 3, 4, 6, \ldots, T \quad (2)$$

$$P_{15}(t) + P_{60}(t) + P^{In}_{Storage}(t) + P^{Out}_{Storage}(t) = 0 \quad (3)$$

In order to ensure that the storage device cannot simultaneously be charged and discharged two binary auxiliary variables $b_1(t)$ and $b_2(t)$ are introduced. During charging operations, $b_1(t) = 0$ and $b_2(t) = 1$. Contrary, during discharging operations, $b_1(t) = 1$ and $b_2(t) = 0$. Eq. (4) then restricts the operation to charging or discharging at any time.

$$b_1(t) + b_2(t) = 1 \quad (4)$$

Eqs. (5) and (6) ensure that the charging- and discharging power flows of the storage device are limited to its rated capacity. Furthermore, they enforce the limitation to either charging or discharging.

$$0 \le P^{Out}_{Storage}(t) \le P^{Capacity}_{Storage} \times b_1(t) \quad (5)$$

$$0 \ge P^{In}_{Storage}(t) \ge -P^{Capacity}_{Storage} \times b_2(t) \quad (6)$$

Constraints (7) and (8) limit the state of charge of the storage device for every timestep t to its energy capacity as well as ensure that it is not discharged below the maximum depth of discharge. Furthermore, these equations also indirectly limit the energy discharge of the storage device to the previously charged energy, taking the efficiency losses into account.

$$\sum_{k=1}^{t} \left(P^{\mathrm{In}}_{Storage}(k) \times \eta^{In}_{Storage} \times \Delta t\right) + \sum_{k=1}^{t} \left(P^{\mathrm{Out}}_{Storage}(k) \times {}^{1}\!/\!\eta^{Out}_{Storage} \times \Delta t\right) \le 0 \quad (7)$$

$$\sum_{k=1}^{t} \left(P^{\mathrm{In}}_{Storage}(k) \times \eta^{In}_{Storage} \times \Delta t\right) + \sum_{k=1}^{t} \left(P^{\mathrm{Out}}_{Storage}(k) \times {}^{1}\!/\!\eta^{Out}_{Storage} \times \Delta t\right) \ge -E^{Capacity}_{Storage} \times \left(1 - \delta_{Storage}\right) \quad (8)$$

**Table 2**
Evaluation parameters and variables.

| | | |
|---|---|---|
| $C^{Invest}_{Storage}$ | [EUR] | Investment cost |
| $N(t)$ | – | Number of realized cycles |
| $L^{Calendric}_{Storage}$, $L^{Cycle}_{Storage}$ | – | Calendric and cycle lifetime |
| $CF(t)$ | [EUR] | Cash flow |
| $r$ | [%] | Discount rate |

The power exchange with the grid and hence the capacity with which the operator participates in the market, is limited to $P^{Limit}_{15}$ and $P^{Limit}_{60}$ using Eqs. (9) and (10).

$$-P^{Limit}_{15} \le P_{15}(t) \le P^{Limit}_{15} \quad (9)$$

$$-P^{Limit}_{60} \le P_{60}(t) \le P^{Limit}_{60} \quad (10)$$

This formulation would enable the operator to simultaneously exploit price differentials between the 15- and the 60-min markets by participating in both markets. In order to exclude this possibility, Eqs. (11) and (12) are modified so that the storage device participates either in the 15- or in the 60-min market by means of an additional binary variable $y(t)$.

$$-P^{Limit}_{15} \times y(t) \le P_{15}(t) \le P^{Limit}_{15} \times y(t) \quad (11)$$

$$-P^{Limit}_{60} \times (1 - y(t)) \le P_{60}(t) \le P^{Limit}_{60} \times (1 - y(t)) \quad (12)$$

### 2.2. Evaluation

The previous optimization formulation is looking only at the dispatch problem, excluding the initial investment effort. For a complete evaluation, all cash flows must be considered. Table 2 summarizes the relevant parameters and variables to conduct this analysis.

The cash flow ($CF$) in period $t = 0$ reflects the investment cost $C^{Invest}_{Storage}$. Frequently the calendric lifetime $L^{Calendric}_{Storage}$ of the storage device is not entirely simulated, but only a shorter timeframe, e.g. due to limited available data. Accordingly, only a fraction of the investment cost should be considered. In addition, some storage technologies – like batteries – are not only constrained by a calendric lifetime limit, but also have operational limits. For simplicity and to derive a formulation which can be used across storage technologies, we will therefore assume a certain number of cycles as an operational limit.

Eq. (13) weights the investment cost with the spent percental calendric or cycle lifetime $L^{Cycle}_{Storage}$, whichever is restricting the expected lifetime of the storage device. $N(T)$ reflects the number of simulated storage cycles until $T$ according to Eq. (14).

$$CF(0) = -C^{Invest}_{Storage} \times \max\left(\frac{N(T)}{L^{Cycle}_{Storage}}; \frac{T}{L^{Calendric}_{Storage}}\right) \quad (13)$$

$$N(T) = \frac{\sum_{n=1}^{T} \left(P^{Out}_{Storage}(n) - P^{In}_{Storage}(n)\right) \times \Delta t}{2 \times E^{Capacity}_{Storage} \times \left(1 - \delta\right)} \quad (14)$$

In line with the discussion in the previous section, if fixed and operation costs are neglected, the cash flow for each time step $t$ is defined by Eq. (15).

$$CF(t) = -P_{15}(t) \times R_{15}(t) - P_{60}(t) \times R_{60}(t) \quad (15)$$

Based on Eq. (15), the Net Present Value (NPV) is determined using Eq. (16). The NPV reflects the current value of a project, taking the

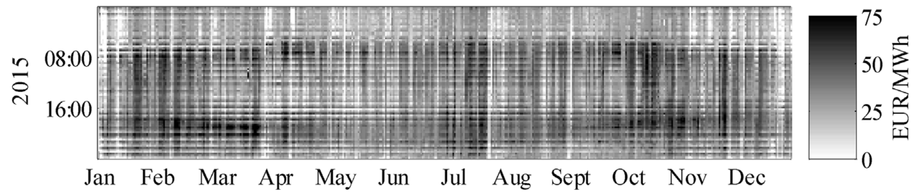


**Fig. 1.** 15-min auction prices along the year 2015.

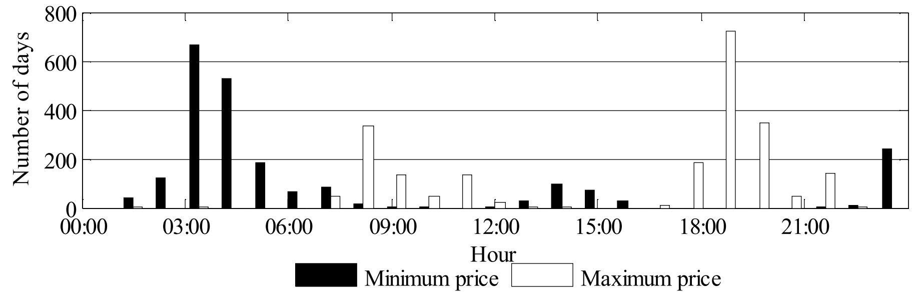


**Fig. 2.** Occurrence of minimum and maximum prices during a day (2011–2016).

time value of money for future cash flows into account by discounting all future cash flows using the discount rate *r*.

$$NPV = \sum_{t=0}^{T} \frac{CF(t)}{(1+r)^{\frac{t\times\Delta t}{8760}}} \quad (16)$$

### 2.3. Hurdle rate

The objective function of the above problem Eq. (1) requires the definition of a hurdle rate to pursue only those opportunities that are sufficiently attractive. To identify the hurdle rate which results in the highest project value and hence NPV, it was implemented a heuristic search routine as follows. The problem of determining the most adequate value for the hurdle rate is assumed to be of concave nature given that for very low hurdle rates a large number of opportunities with low revenue contribution will be pursued, reducing the expected lifetime of the storage device and hence resulting in a low NPV. Contrary, for very high hurdle rates, the dispatch algorithm becomes very selective and only few opportunities are pursued, resulting also in a low NPV. Therefore, Algorithm 1 represents a simple hill-climbing search that iteratively narrows the search space until a sufficiently precise solution is obtained.

**Algorithm 1.** Iterative search routine to determine the optimum hurdle rate

1. Definition of the initial search range for the hurdle rate
2. Partition of the search space by n equally spaced search points
3. Determination of the NPV for each search point by solving the associated MIP detailed in Section 2.1
4. Identification of the search point with the highest NPV
   a. In case the optimum search point is at either end of the search range: define the new search range from the end of the current range to the adjoining search point
   b. Otherwise: the new search range is defined by the two adjoining search points to the optimum point
5. Repeat steps 2–4 until the width of the search range gets smaller than a predefined threshold

### 2.4. Implementation

For longer time horizons, solving the above described MIP becomes computational expensive. This issue is aggravated as the MIP needs to be solved multiple times to determine the optimum hurdle rate. Therefore, the problem is broken into multiple smaller problems, each covering a time period with the duration of *w* time steps. To ensure that the problem identifies a good quality solution when compared to the optimum solution of the entire problem, we considered an overlapping window with a length of *x* time steps for each sub-problem. The first period therefore stretches from $t = 1 \ldots w + x$, allowing to include information for x time steps of the next period. The second period then considers the period from $t = w + 1 \ldots 2w + x$, and so on. To account for the daily periodicity of the demand, of prices as well as for the typical charge and discharge patterns of storage devices, *w* was set to one day and the overlapping window *x* is also set to one day. However, these parameters have to be chosen in accordance with the capacity of the analyzed storage system as well as the price dynamics of the considered electricity markets. As described in Ref. [15], this strategy ensures that the error between the approximate solution and the exact solution for the unbroken problem is less than 1% while the computational cost is reduced significantly.

## 3. Case study — data and assumptions

Although the developed model is general, for the forthcoming analysis we considered the short-term electricity market for Germany, which is operated by the European Power Exchange, and where both 60- and 15-min auctions are available. For the 60-min auctions, we analyzed the data from the years 2011 until 2016, and from 2015 until 2016 for the 15-min contracts. Overall, market prices have declined over the last years. The average price for the 60-min auction declined from 51 EUR/MWh in 2011 to 29 EUR/MWh in 2016. At the same time, the number of hours with negative prices increased from 15 h in 2011 to 97 h in 2016.

Fig. 1 shows the evolution of the 15-min auction results along 2015. It is obvious that prices during the night are typically lower, followed by a first peak around 8:00 a.m. and again by 19:00 p.m. In summer, prices during the afternoon are typically also lower. This pattern is persistent along the years for both the 15- and 60-min auctions.

Fig. 2 shows the temporal occurrence of the daily minimum and maximum prices. A common operation pattern for the storage device is hence to be charged during the night and be discharged in the evening. During some days, another opportunity exists with an additional cycle covering the morning peak and the afternoon valley.

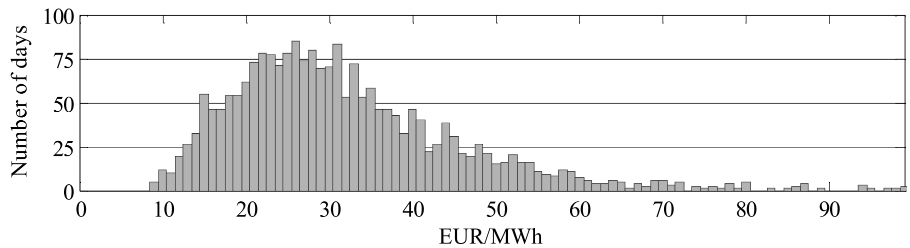


**Fig. 3.** Difference between daily minimum and maximum price for 1-h contracts (2011–2016).

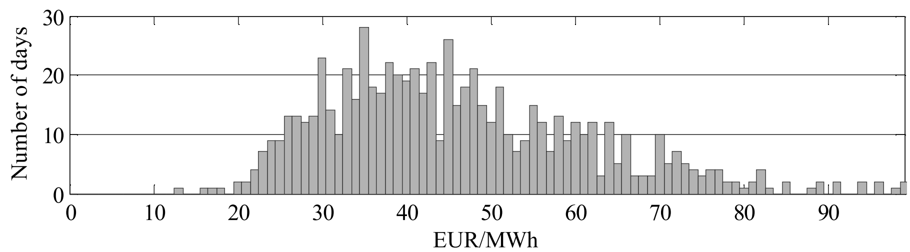


**Fig. 4.** Difference between daily minimum and maximum price for 15-min contracts (2015–2016).

Figs. 3 and 4 show the difference between the maximum and minimum prices for each day for the 60-and 15-min auctions. It is obvious that the latter has a significantly wider daily price range and hence – neglecting technical considerations – offers a greater revenue potential when considering the daily operation cycle of a storage device. However, in line with the overall price decrease, the daily spread has also slightly decreased over the last years.

For the following analysis, we considered a lithium-ion battery with a power rating ($P_{Storage}^{Capacity}$) of 1 MW and a nominal energy capacity ($E_{Storage}^{Capacity}$) of 1.25 MWh. With a maximum depth of discharge ($\delta_{Storage}$) of 20%, the effective storage capacity is 1 MWh. The charge- and discharge-efficiencies ($\eta_{Storage}^{In}$ and $\eta_{Storage}^{Out}$) are assumed to be 94.87% each, resulting in a round-trip efficiency of 90%. Calendric lifetime ($L_{Storage}^{Calendric}$) is assumed to be 15 years and the expected cycle lifetime ($L_{Storage}^{Cycle}$) is set at 5000 cycles. The assumed capital expenditure for the system ($C_{Storage}^{Invest}$) is estimated at 1 250 000 EUR [16].

## 4. Results

### 4.1. Maximum revenues

In a first step, this analysis neglects the investment cost in order to determine the maximum potential revenue. Therefore, the hurdle rate of the objective function is set to zero thus ensuring that all possible arbitrage opportunities are pursued. Furthermore, by selectively setting $P_{15}^{Limit}$ and $P_{60}^{Limit}$ to zero, the revenues for both markets can be individually determined. The obtained revenues are summarized in Fig. 5.

Participating only in the 60-min auction resulted in annual revenues ranging from 9278 EUR to 15 502 EUR. The 15-min auctions are a more attractive alternative, with significantly higher potential revenues (43 169 EUR in 2015 and 29 200 EUR in 2016) which is in line with the larger price spreads in the 15-min auction as illustrated in Fig. 4. Dispatching the storage device simultaneously in both markets further improves the revenue potential, but the additional gains are not significant (+1% in 2015, +2% in 2016). Given the investment cost of 1.25 MEUR, it is very unlikely that the storage device can break-even during its calendric lifetime of 15 years in any of the analyzed markets.

The higher revenues in the 15-min market go hand in hand with a significantly higher number of operations, indicated by the number of performed cycles in Fig. 6. While the storage device was on average charged- and discharged twice a day in the 60-min market, about 8 complete cycles were completed in the 15-min auction. Setting revenues and realized cycles into relation, the 60-minute market is more attractive with average revenues per cycle of 17.46 EUR versus only 12.57 EUR in the 15-min market. Hence, while more opportunities exist and are exploited by the algorithm in the 15-min market, these frequently contribute only marginally to the total revenues.

Assuming the dispatch in the 15-min auction, after two years of operation the storage device would be at the end of its cycle lifetime with more than 5700 realized cycles. However, the obtained revenue would still be significantly short to break-even given the initial investment. As the calendric lifetime would allow for a substantially longer operational life, the operator should be more selective when dispatching the storage device thus suggesting that an adequate value for the hurdle rate should be adopted.

### 4.2. Maximum profitability

In order to determine the benefit of a storage investment, we will now focus on the evaluation of the maximum profitability. Contrary to the previous analysis, which only focused on the available revenues, now we are also taking into account the cost of the storage device. As there is not sufficient data for an evaluation over the complete lifetime of the storage device available, the investment cost associated to the evaluated time span is determined using Eq. (13). Hence, the storage device will be depreciated according to its usage to reflect the dual limitation resulting from both the calendric and cycle lifetime. The resulting NPV will therefore not reflect the entire value of the storage investment, but only for the analyzed period. To simplify the analysis, $r$ was assumed to be zero to neglect the time-value of money.

In order to determine the maximum NPV, we used Algorithm 1 to identify the optimum hurdle rate which balances realized cycles and the resulting depreciation of the storage device. Fig. 7 shows how the process iteratively determines the hurdle rate that leads to the maximum NPV. It is obvious that the relationship between the hurdle rate and the NPV is smooth, hence small deviations from the exact value will not change the result dramatically. This is relevant, as the determination of the optimal rate is based on historical data, whereas the storage dispatch relies on forecasts.

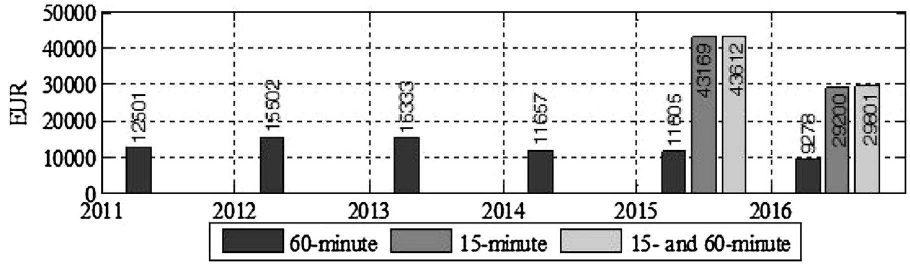


**Fig. 5.** Maximum revenues from 2011 to 2016.

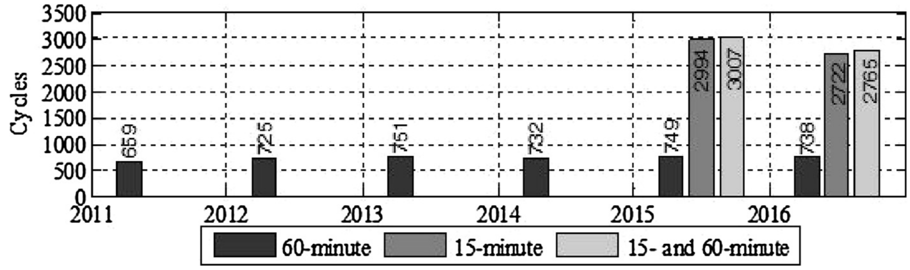


**Fig. 6.** Performed cycles from 2011 to 2016.

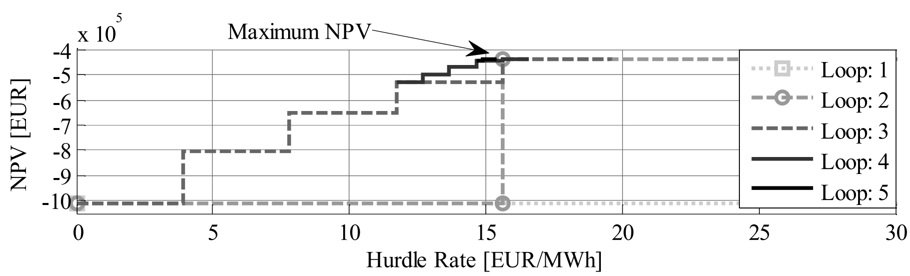


**Fig. 7.** Search process to identify optimum hurdle rate.

For the 60-min market, a hurdle rate of 15.14 EUR was found to maximize NPV. As a result, the average annual number of realized cycles was more than halved from 725 cycles per year to only 330. Considering the 15-min market, a significantly higher hurdle rate of 28.32 EUR should be used to maximize NPV, resulting in a decrease of the average annual cycles from 2858 to 330. Dispatching in both markets simultaneously further increased the optimal hurdle rate to 28.48 EUR.

In both markets, the optimal number of operations was found to be 330. The optimal strategy is to focus on the most attractive opportunities and operate the storage device only so often such that calendric aging and wear-down from operations get balanced. Therefore, at the end of its calendric lifetime the storage device also reaches its cycle lifetime limit.

Fig. 8 shows the resulting revenues considering the hurdle rates. For the 60-min market, the overall revenues decreased by only 20%. Operations in the 15-min market or in both markets at the same time experience a revenue reduction of about 60%, however still remaining more attractive than the 60-min market.

The average annual depreciation cost amounts to 83 333 EUR, significantly higher than the obtainable revenues in any year. Hence, even pursuing only the most attractive opportunities and neglecting the time-value of money, the use of electric storage devices to pursue arbitrage operations remain highly unattractive from a financial perspective. Assuming the same revenue potential for the future, the available revenues are not sufficient to justify a storage investment.

### 4.3. Sensitivity analysis

In a next step, a sensitivity analysis was conducted to determine the optimal ratio of power- and energy capacity. For the following analysis, efficiency losses as well as the depth of discharge were assumed to be zero and the dispatch was done using the hurdle rate values determined in Section 4.2. Fig. 9 shows the financial impact of modifying the power capacity $P_{Storage}^{Capacity}$ for a given energy capacity $E_{Storage}^{Capacity}$.

For the 60-min auction, increasing the power capacity beyond the energy capacity is not beneficial, as the additional power capacity cannot be utilized. Decreasing the power also has a relatively limited impact for initial reductions. In fact, a reduction of the power capacity by 75% would only lead to a revenue reduction of 27%. However, beyond this point, the impact becomes significantly more pronounced. If the power capacity is reduced by 90% (i.e. it would take 10 h to fully charge the storage device), revenues would be less than half of the original ones.

Looking at the 15-min auction, increasing the power capacity beyond the energy capacity can be useful in order to fully charge or discharge the storage device within less than one hour. Fig. 9 shows a strong increase in revenues if the charging-/discharging period is reduced from one hour (base case) to 30 min (+75% points) or 15 min (+161% points). A decrease in power capacity leads to a much quicker deterioration of revenues than in the 60-min market, indicating that the revenues in the 15-min auction are strongly influenced by exploiting the most extreme prices.

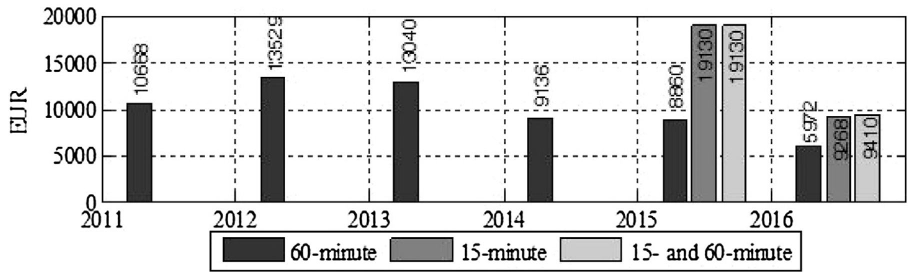


**Fig. 8.** Revenues considering a hurdle rate.

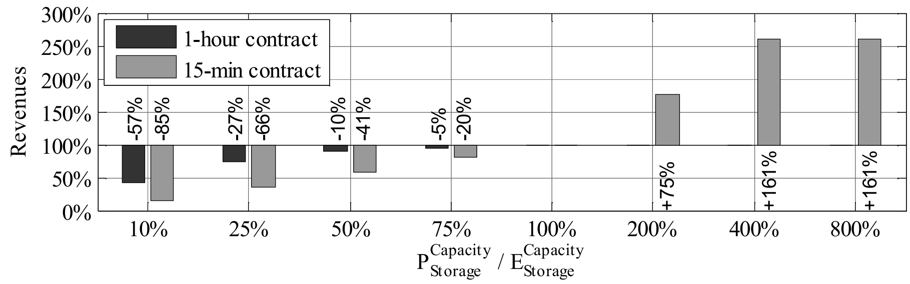


**Fig. 9.** Optimal power to energy capacity ratio.

## 4.4. *Spatial arbitrage*

Apart from the previously discussed inter-temporal arbitrage, arbitrage can also be pursued on a spatial dimension exploiting price differentials between two different markets. In this case, the immediate arbitrage between the 15- and 60-min auctions for the German market is considered. Hence, no storage capacities are required. Considering the constraints defined by Eqs. (9) and (10) instead of Eq. (11) and (12), the previously defined MIP permits immediate arbitrage between these markets. Setting $P_{15}^{Limit}$ and $P_{60}^{Limit}$ to 1 MW and ignoring the storage device by setting $P_{Storage}^{Capacity}$ to 0, the revenues without a storage device can then be estimated. We obtained values of 18 666 EUR and 17 011 EUR for 2015 and for 2016.

Fig. 10 compares the revenue potential of dispatching a storage device to benefit from temporal price differences (as presented in the previous sections), exploiting price differences between the 15- and 60-min markets without a storage device as well as pursuing both strategies simultaneously. In both years, the revenues could be increased significantly. However, due to the assumed power limitation of 1 MW, the results obtained for the combined operation do not correspond to a linear combination of the results with and without considering storage, but a revenue gap remains.

As a conclusion, pursuing spatial arbitrage between the 15- and 60-min markets is a viable strategy, especially considering that no investments are required. Furthermore, if an operator installs a storage device for arbitrage the revenues from spatial arbitrage can be significantly enlarged.

# 5. Price volatility to break-even

In this section we will analyze which price volatility is required for a storage device dispatched for arbitrage in order to reach the break-even point. Therefore, first a price simulation process was developed and calibrated to historic market prices. Following, the parameters of the process will be modified to simulate market prices, until the previously mentioned storage device reaches the break-even point.

## 5.1. *Price simulation*

In order to easily adjust the parameters of the price evolution process, additive decomposition [17–19] was used to break the process into three components: a deterministic process to capture the trend and seasonal behavior, $X(t)$, price jumps, $J(t)$, and stochastic residuals, $S(t)$. For each of them, it was derived a mathematical model and the parameters were estimated from historical data for the years 2011 to 2016.

### 5.1.1. *Trend and seasonality*

Over the time-horizon of several years, prices frequently display an evolution toward higher/lower prices. In the presented model, this is included as a linear trend. In addition, the following seasonal patterns of electricity prices are considered: annual period (demand and supply fluctuate between the different seasons, driven by e.g. the outside temperature and the availability of renewable resources), weekly period (demand during the weekend typically differs from the demand pattern during the week days) and daily period (demand also varies significantly along the day). In addition, a significant generation resource (solar generation), is also only available during daytime.

These periodic patterns can be decomposed into sine- and cosine-functions, as shown by Eq. (17) for hourly contracts. In this expression, $\alpha_0$ reflects the permanent price level, and $\alpha_1$ is the coefficient of the overall long-term linear trend. The annual periodic behavior is described by the coefficients $\alpha_2$–$\alpha_5$, the weekly cycle by coefficients $\alpha_6$–$\alpha_9$ and the price patterns within a day by $\alpha_{10}$–$\alpha_{13}$.

$$\begin{aligned}
X(t) &= \alpha_0 + \alpha_1 t + \ldots \\
&\alpha_2 \cos(\frac{2\pi t}{365}) + \alpha_3 \sin(\frac{2\pi t}{365}) + \alpha_4 \cos(\frac{4\pi t}{365}) + \alpha_5 \sin(\frac{4\pi t}{365}) + \ldots \\
&\alpha_6 \cos(\frac{2\pi t}{7}) + \alpha_7 \sin(\frac{2\pi t}{7}) + \alpha_8 \cos(\frac{4\pi t}{7}) + \alpha_9 \sin(\frac{4\pi t}{7}) + \ldots \\
&\alpha_{10} \cos(2\pi t) + \alpha_{11} \sin(2\pi t) + \alpha_{12} \cos(4\pi t) + \alpha_{13} \sin(4\pi t)
\end{aligned} \tag{17}$$

The coefficients $\alpha_0$–$\alpha_{13}$ can be estimated using a linear regression process. Fig. 11 shows the distribution of residuals after removing

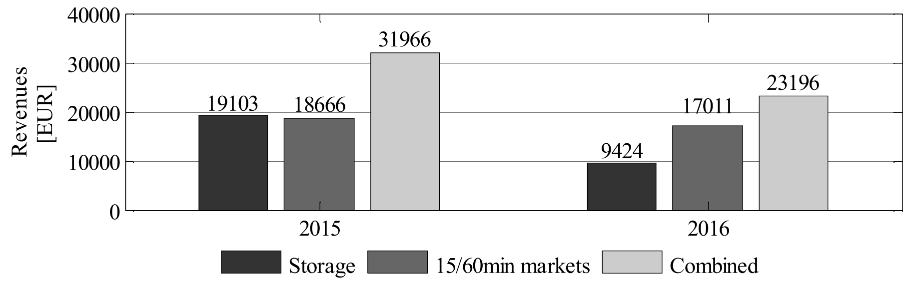


**Fig. 10.** Revenue comparison between intertemporal and spatial arbitrage.

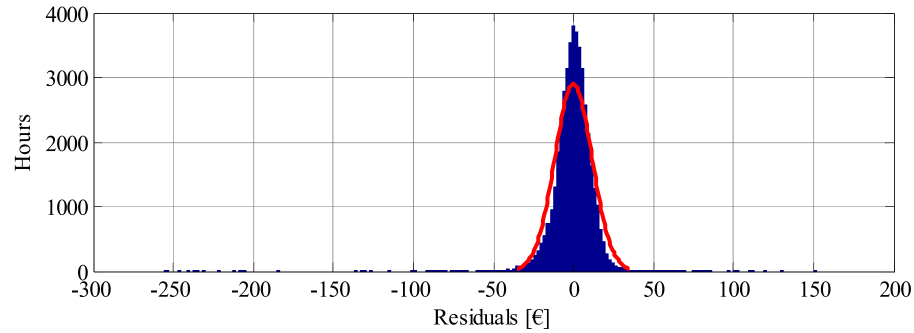


**Fig. 11.** Distribution of price residuals after removing the seasonal components.

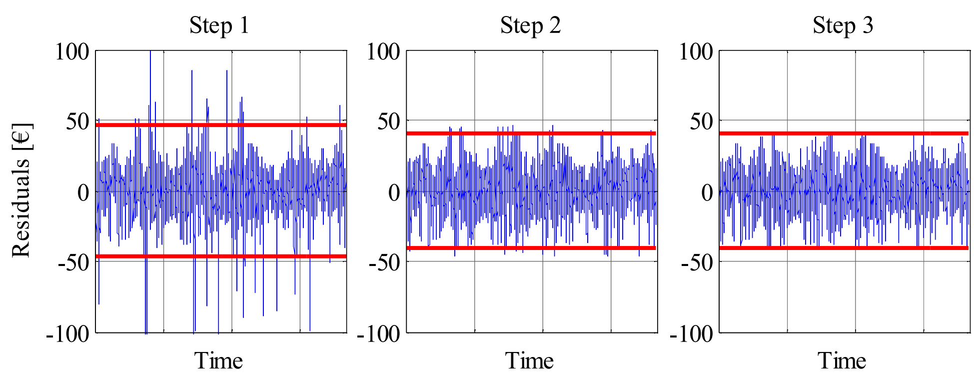


**Fig. 12.** Process to remove jumps from price series over three iterations.

the seasonal components from the time series. The residuals have a mean of 0, but are slightly skewed to the left.

### 5.1.2. Jumps

After identifying the deterministic trend $X(t)$, the residual time series is analyzed for price jumps determining in the first place the standard deviation of the residual series. Then, all prices outside a specified confidence interval (in this case $\pm 4\sigma$) are assumed to be jumps and are removed from the time series. This process is repeated until no more outliers are present, as shown by Fig. 12 for the first three iterations. Fig. 13 shows the distribution of the removed jumps, which will be modeled by an exponential distribution (with parameters $\lambda_{jump\_up}$ and $\lambda_{jump\_down}$) shifted by a constant ($\alpha_{jump\_up}$ and $\alpha_{jump\_down}$).

Weron [20] suggests that price spikes are subject to seasonality and occur more frequently during high price periods. However, this author also acknowledges that the scarcity of occurrences turn the identification of relations and the integration into a model problematic. Therefore, the occurrence of price jumps is assumed to be independent and governed by their empiric probability ($\delta_{jump\_down}$ and $\delta_{jump\_up}$). The model for the price jump process $J(t)$ is shown by Eq. (18).

$$J(t) = \left(\alpha_{jump_{up}} + \exp\left(\lambda_{jump_{up}}\right)\right) \times j_{up} + \left(\alpha_{jump_{d}own} + \exp\left(\lambda_{jump_{d}own}\right)\right) \times j_{down}$$
$$\text{with}\, j_{up} = 1 \text{ with probability } \delta_{jump_{up}},\ \text{otherwise}\, j_{up} = 0$$
$$\text{with}\, j_{down} = 1 \text{ with probability } \delta_{jump_{d}own},\ \text{otherwise}\, j_{down=0} \tag{18}$$

### 5.1.3. Stochastic residuals

Fig. 14 shows the remaining residuals after removing both the deterministic component and the price jumps. They are almost normally distributed, however exhibiting a strong autocorrelation.

To model these stochastic residuals, an autoregressive first order model (AR(1)) [21] was chosen, as described by Eq. (19). The term $\varepsilon(t)$ is assumed to be normally distributed with a mean of zero. While empirical evidence suggests that volatility is not constant, integrating heteroscedasticity into the model does not necessarily lead to better accuracy [20]. Therefore, a constant volatility of $\sigma_\varepsilon$ is assumed. Both $\sigma_\varepsilon$ as well as the coefficient $\alpha$ can easily be estimated from historical data by using linear regression.

$$S(t) = \alpha \times S(t-1) + \varepsilon(t) \tag{19}$$

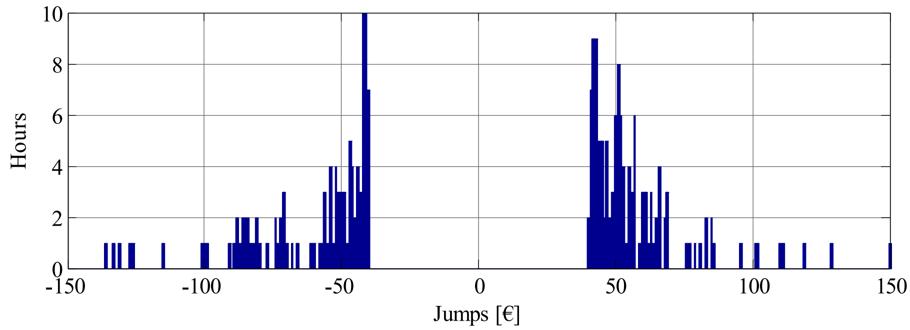


**Fig. 13.** Distribution of identified and removed price jumps.

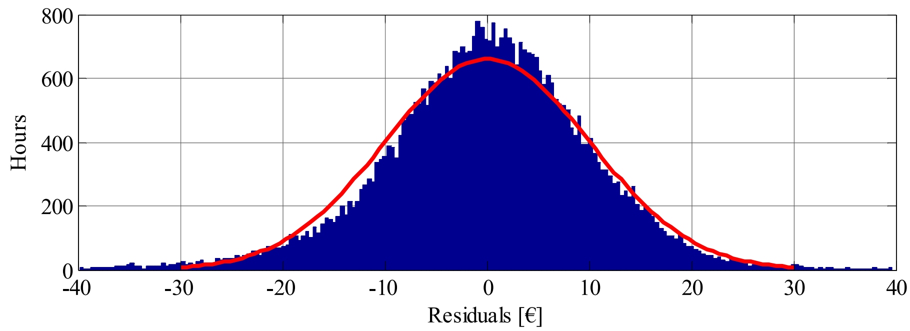


**Fig. 14.** Distribution of price residuals after removing the seasonal and the price jump components.

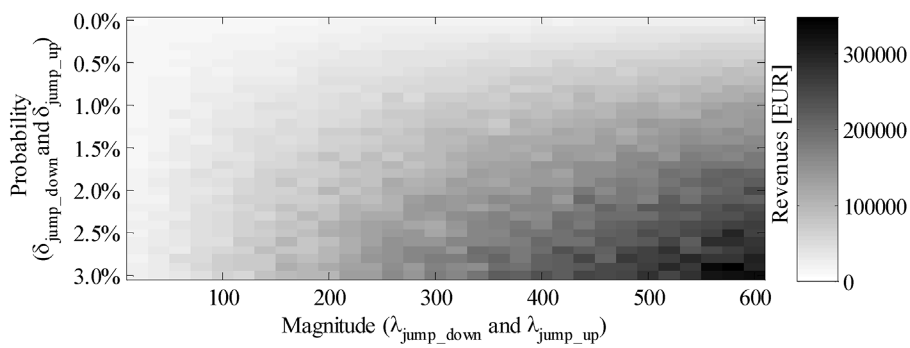


**Fig. 15.** Annual revenue potential.

*5.1.4. Simulation*

Once all required parameters were estimated from historical data, the additive decomposition is reversed. All three components are modeled individually, and aggregated at the end to obtain the simulated price path as indicated by Eq. (20).

$$R(t) = X(t) + J(t) + S(t) \tag{20}$$

Care must be taken when selecting the data which is being used for the calibration of the model. If the considered period is too long, recent changes might be given too little weight. Contrary, if the period is too short, the recent price changes might be given too much importance. In this case, five years of data was used to reflect the increase of renewable generation capacity over the recent years.

## 5.2. Analysis

Arbitrage revenues are driven by the occurrence and the magnitude of price jumps. For the jump process $J(t)$, the probability that a jump occurs in any time-step was estimated to be about 0.3% both for up- as well as down-jumps. The constant shift was estimated to be about ±40 EUR. Jumps toward lower prices showed a significant higher magnitude (−34 EUR) than jumps to higher prices (+15 EUR).

In the following, these parameters are modified in order to identify the volatility that is required in order to ensure the break-even of the storage device. Therefore, the jump probability and the parameter of the exponential distribution are increased stepwise and for each setting a synthetic price path is simulated. Following, for each case the optimal dispatch is determined to check if break-even was reached or not. Fig. 15 shows the obtained revenues in the hourly market. In order to reach the required revenues to break-even, price jumps would have to occur approximately 7 times as frequent as well as 7 times as distinctive as it is currently implicit in the historic prices that were initially used.

However, a higher volatility would further increase the difficulty of predicting future prices as well as the identifying the optimum dispatch. Hence, an even stronger increase is likely required to consider the imperfect precision of price predictions. Furthermore, the increasing revenue potential would make arbitrage operations economically more attractive. The participation of additional market agents however would have a smoothing effect on prices, again reducing volatility and revenue potential.

## 6. Conclusions

This paper analyzes the potential application of storage to pursue price arbitrage namely focusing on the 60- and the 15-min auctions that integrate the German market model. This analysis included the development of a dispatch model to simulate the operation of the storage device in only one market or in both simultaneously. Although the revenues increase when operating also in the 15-min auction, the results show that the revenues are not enough to justify the investment cost. This research also included the analysis of spatial price arbitrage profiting from price differences between the two mentioned intraday markets. Since this does not require installing a storage device and so no investment costs have to be accommodated, this appears to be an interesting business alternative. Finally, it was estimated the required price volatility in the 60-min German intraday market that would break-even an investment in an 1 MW storage device. The analysis indicates that both the probability and the magnitude of the price jumps would have to increase by 7 times regarding historic values to ensure break-even assuming the current value of investment cost in storage. Given the relevance of this increase, it appears much more likely that future investment cost reductions in storage devices, namely in lithium-ion batteries, will contribute more rapidly to turn storage applications more interesting from an economic point of view. Furthermore, future research in this context should consider the validity and effect of the assumption that future prices are known ahead of time or can be forecasted with precision.

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