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Battery Storage Optimization on the German Continuous Intraday Market: An Experimental Analysis under Consideration of Price Uncertainties

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Abstract. This article uses an experimental approach to examine the extent to which price fluctuations influence the profitability of electricity storages operating on the German Continuous Intraday Market. For this reason, we are extending our previous research and analyzing the trade-off between storage capacity and price forecast uncertainty with regard to arbitrage profitability. Using a genetic algorithm, we optimize buy and sell decisions for different battery storage sizes and simulated price forecast uncertainties over the year 2021. Our results show that a storage management strategy generated by the genetic algorithm enables significant arbitrage revenues, which rise in particular with increasing storage capacity. However, with an increasing battery size, decreasing marginal profits are to be expected. Price uncertainties due to forecast errors also reduce the gains, but their influence on profit remains moderate compared to the storage size. The genetic algorithm used provides an intelligent strategy for optimizing storage usage even under uncertain market conditions.
Keywords: Continuous Intraday Electricity Market, Genetic Algorithm, Arbitrage Trading, Agent, Battery Storage Optimization, Price Uncertainties.

1 Introduction

The steady expansion of renewable energy sources (RES) not only leads to increased participation in increasingly short-term markets but also requires a more flexible supply of electricity in periods when less electricity is generated. In Germany, as of 2024, a total of 1.497 gigawatts of battery energy storage systems (BESS) with a nominal capacity of over 1 MW have been installed [1]. The trend is likely to increase significantly over the next years, particularly for large storage systems, to be able to shift much larger quantities of electricity to periods with little sun and wind [2]. While participating in the balancing energy market (reserve) is initially obvious, trading on the spot markets will also become more attractive due to increased price levels, fast response

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times, and falling storage prices [3], [4]. The intraday market (IDM), which offers market participants the last opportunity before delivery to optimize their portfolio and therefore has high liquidity, particularly in the last few hours before delivery, is likely to be of considerable interest here [5]. The products are traded at hourly, half-hourly, and quarter-hourly intervals, allowing a customized optimization of the electricity portfolio. In certain instances, there is significant volatility in electricity prices, rendering the utilization of battery storage a financially viable option (Figure 1).

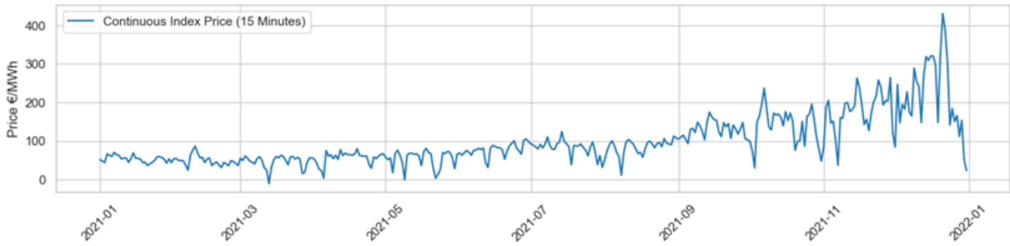

Figure 1. Annual price view for 15-minute products in Germany 2021 (aggregated to days)

In recent studies, various strategies have already been evaluated to generate profits on the IDM through pure trading without own electricity production. This mostly risk-free or low-risk exploitation of price differences is also known as arbitrage trading. Basically, IDM threshold-oriented methods [6] or various approaches like pair trading, e.g., in combination using the greedy method [7], [8] can be mentioned. These pair trading methods are designed to ensure that buy and sell decisions are matched together evenly , either in the same control area or across control areas, so that price differences can be exploited profitably.

An emerging branch in the field of arbitrage trading is the application of artificial intelligence using deep reinforcement learning [9]–[12]. Here, for instance, Bertrand and Papavasiliou were able to show with their experimental setup that machine learning methods in connection with heuristics (Markov Decision Process) can outperform comparable benchmarks in terms of profitability on the German IDM [12]. It is important to note that in [12], as in [13], [14], trading was simulated on a contract level. This contract data from the limit order book is important for in-depth analyses, which can also be used to explain revenue losses of BESS, for instance, due to bid-ask spreads [15], [16].

Longer-standing literature has largely failed to identify profit opportunities for long-term arbitrage-only applications with storage [17], [18]. This was due to high investment costs for storage technologies or too few times when the price spread would be high enough for such trading options. However, more recent studies show that arbitrage transactions can now be one of the main sales drivers for battery storage in electricity markets [11], [19] and are likely to play an important role in the competitiveness of energy storage if storage prices continue to fall [20]. The choice of battery characteristics also plays a major role here, determining the charging and discharging speed and capacity, and thus the intended use of the battery.

The aim of this article is to evaluate the extent to which battery size and price fluctuations on real-time markets affect potential profitability. In this regard, we are building on and extending our previous article [21]. In an experiment, we consider different sizes of intraday-only battery storage systems on the German intraday market, which use a genetic algorithm (GA) to make buy and sell decisions over the course of a year. For this purpose, we use a simplified framework of real-time trading based on volume-weighted prices, which offers high flexibility and delivers sufficiently good results with little effort. In addition, we also include price deviations to influence and test the decision-making component of our algorithm. Actual costs, such as possible grid charges or trading fees, are not considered in this scenario. The scope of application is limited to the German intraday market. For the most part, however, this approach should also be applicable to other European markets.

The article is organized as follows. Characteristics of the continuous intraday market are briefly explained in Section 2. The proposed decision model is discussed in Section 2, and a corresponding genetic algorithm is presented in Section 4. The experimental results are available in Section 5. Brief discussion and conclusion are provided in Section 6 and Section 7, respectively.

2 Characteristics of the Continuous Intraday Market

The EPEX Spot Continuous Intraday Market (IDM) in Germany is a central component of European electricity trading and is operated by EEX AG, one of the largest energy exchanges in Europe. This market enables market participants to trade electricity products for the current day in near real time and to react quickly to changes in the schedule or forecast deviations. The IDM therefore comes after the day-ahead market (DAM), on which trading takes place one day earlier. The main difference between the two markets is the way in which the trades are processed. While all bids for all hours of the following day must be submitted at 12 noon on the DAM and a unit price for each hour is announced shortly afterwards, trading on the IDM is continuous [22].

This means that a bid can be placed for any product at almost any time from the start of trading, provided it is not in the past. The bids of the trading participants are brought together in real time using a matching algorithm. The price determination procedure here is pay-as-bid. Traded products are hourly, half-hourly, and quarter-hourly. A special feature of the German IDM is its different trading phases. While most real-time markets, at least in Europe, close half an hour before delivery, in Germany, trading can continue up to 5 minutes before delivery in the respective control area. There is a total of four of these control zones [23].

This study will focus exclusively on quarter-hourly products. For further information on the market, we recommend the article by Kiesel and Paraschiv, who have examined the characteristics of quarter-hourly products at IDM in detail [24].

As the intraday market is subject to significantly higher short-term fluctuations than the previous markets, it harbors both more risk and higher profits. The first companies with intraday battery storage systems are already active on the market and are taking advantage of this high-risk, high-reward characteristic. In this article, we will deal exclusively with the intraday market. This means that our agent could theoretically submit a bid for a product at any time. A bid on the IDM has four basic characteristics:

1. A delivery start and a delivery end, in which electricity is fed in or out evenly.
2. An order type, i.e., whether the bid is a buy or a sell.
3. The price for the product in €/MWh.
4. The quantity to be traded (in MWh).

Further properties can be added for cross-border trading or transactions across control areas (delivery area). However, these are not considered in this analysis.

3 Decision Model

To estimate the revenue potential of arbitrage trading with and without a battery, we need to define the framework conditions that will apply in this experiment:

1. Since in continuous trading it is possible to trade almost any product at any time, the potential solution space is infinite. We therefore need fixed points in time at which trading is to take place. For this purpose, we have chosen a time window of 15 minutes. This means that the agent makes a decision every 15 minutes for all products that lie within its current decision range.
2. The first condition raises the question of the price at which a product should be traded. This is because pricing according to the pay-as-bid principle can quickly result in different prices, even at the same time. While similar contributions use real bids [12], we use the volume-weighted price of all bids in 15-minute time periods for the respective product at the relevant time grid. Of course, this has the disadvantage that it is never certain that a trade could really be executed at exactly this price.

3. We only consider the 15-minute products on the intraday market, as these are particularly susceptible to short-term changes in RES. We also assume that our participation in the market has no influence on prices and that every trading request made by the agent can be realized.
4. The trading strategy used should be balanced and feasible. This means that the agent should only ever make decisions that do not exceed the storage, in- and outfeed capacity. At no time should more trades be concluded than could be delivered. In a real scenario, failure to comply with a contract would result in penalty costs (REBAP) and must be considered by the algorithm.
5. The test setup should be kept simple. For this reason, the agent always trades in fixed volumes. Loss of efficiency, as used in [11], is not considered. An implementation of efficiency loss is possible in principle, but would make the experiment more difficult and lead to unwieldy values in purchasing and sales. The same applies to operating costs such as grid fees, trading fees, or acquisition costs.
6. To represent price uncertainties, prices that are used for future decisions are randomly distorted by a variable factor. However, prices at the current point in time are known and related products can be bought or sold as planned.

The agent should now act in this environment by making decisions on a rolling basis. The time window considered in the experiment is the entire year 2021, from January 1 up to and including December 31. This year is characterized by the increased price level (see also Figure 1), which peaked in 2022 [33]. The model aims to illustrate the possible actions of a decision-maker on the IDM who has a limited battery capacity and wants to maximize their total revenue. In this experiment, the storage system can only ever be charged or discharged by a percentage of its maximum capacity *vlimit* within a partial period. The decision horizon considered at a point in time comprises $t = 1, 2, \ldots, T = 96$ periods per day (d). Within each period, action segments (a) can be carried out or planned for associated products (s).

$J^{d,t}$ forms an action matrix (Figure 2) which represents all decisions during the planning horizon for the relevant part of the trading day, and can take the following forms (Expression 1):

$$J_{a,s}^{d,t} = \begin{cases} 1, on\ purchase \\ -1, on\ sale \\ 0, do\ nothing \end{cases} \tag{1}$$

Greyed-out boxes represent actions that were in the past and are therefore infeasible. The action section a = 0 always represents the actual situation, and therefore the real prices are known exactly, whereas the price data of products (s = 1, 2, …, S) for actions a > 0 have to be estimated. Real and estimated prices are shown in the analogue price matrix $P^{d,t}$ (Figure 3).

In order to determine the related prices, we use volume-weighted prices for each product at quarter-hourly intervals. For calculating the prices, we follow the notation of the article by Narajewski and Ziel [25]. For instance, a volume-weighted price ${}_{x}ID_{y}^{d,s}$ can be calculated for a product s on day d using the EPEX SPOT data (Expression 2). Here, x and y delimit the period of the trades considered for this product, where $x \geq 0$ and $y > 0$. $\mathbb{T}_{x,y}^{d,s}$ forms the time window under consideration, which can be set to the last 15 minutes before delivery with $x = 0$ and $y = 0.25$, for instance.

$${}_{x}ID_{y}^{d,s} := \frac{1}{\sum_{k \epsilon \mathbb{T}_{x,y}^{d,s}} V_{k}^{d,s}} \sum_{k \epsilon \mathbb{T}_{x,y}^{d,s}} V_{k}^{d,s}\ P_{k}^{d,s} \tag{2}$$

The volume-weighted price *ID* is formed from the respective volumes (*V)* with the corresponding prices (*P*) of all contracts (*k*) that come into existence during this period. The prices can also be differentiated by every action step (*a*). The last 5 minutes, in which trading is no longer possible, are not excluded in this article, as no data is available for this timespan. Figure 3 shows a corresponding example of such a price matrix.

Product

Actions	$s=0$	$s=1$	$s=2$	$s=3$	$s=4$	$s=5$	$s=6$	$s=7$
$a=0$	$J^{d,t}_{a,s}$	$J^{d,t}_{a,s=1}$	$J^{d,t}_{a,s=2}$	$J^{d,t}_{a,s=3}$	$J^{d,t}_{a,s=4}$	$J^{d,t}_{a,s=5}$	$J^{d,t}_{a,s=6}$	$J^{d,t}_{a,s=7}$
$a=1$		$J^{d,t}_{a=1,s=1}$	$J^{d,t}_{a=1,s=2}$	$J^{d,t}_{a=1,s=3}$	$J^{d,t}_{a=1,s=4}$	$J^{d,t}_{a=1,s=5}$	$J^{d,t}_{a=1,s=6}$	$J^{d,t}_{a=1,s=7}$
$a=2$			$J^{d,t}_{a=2,s=2}$	$J^{d,t}_{a=2,s=3}$	$J^{d,t}_{a=2,s=4}$	$J^{d,t}_{a=2,s=5}$	$J^{d,t}_{a=2,s=6}$	$J^{d,t}_{a=2,s=7}$
$a=3$				$J^{d,t}_{a=3,s=3}$	$J^{d,t}_{a=3,s=4}$	$J^{d,t}_{a=3,s=5}$	$J^{d,t}_{a=3,s=6}$	$J^{d,t}_{a=3,s=7}$
$a=4$					$J^{d,t}_{a=4,s=4}$	$J^{d,t}_{a=4,s=5}$	$J^{d,t}_{a=4,s=6}$	$J^{d,t}_{a=4,s=7}$
$a=5$						$J^{d,t}_{a=5,s=5}$	$J^{d,t}_{a=5,s=6}$	$J^{d,t}_{a=5,s=7}$

Figure 2. Formal representation of an action matrix

Product

Actions	$s=0$	$s=1$	$s=2$	$s=3$	$s=4$	$s=5$	$s=6$	$s=7$
$a=0$	${}^{a}_{0}ID^{d,s}_{0.25}$	${}^{0}_{0.25}ID^{d,1}_{0.25}$	${}^{0}_{0.5}ID^{d,2}_{0.25}$	${}^{0}_{0.75}ID^{d,3}_{0.25}$	${}^{0}_{1}ID^{d,4}_{0.25}$	${}^{0}_{1.25}ID^{d,5}_{0.25}$	${}^{0}_{1.5}ID^{d,6}_{0.25}$	${}^{0}_{1.75}ID^{d,7}_{0.25}$
$a=1$		${}^{1}_{0}ID^{d,1}_{0.25}$	${}^{1}_{0.25}ID^{d,2}_{0.25}$	${}^{1}_{0.5}ID^{d,3}_{0.25}$	${}^{1}_{0.75}ID^{d,4}_{0.25}$	${}^{1}_{1}ID^{d,5}_{0.25}$	${}^{1}_{1.25}ID^{d,6}_{0.25}$	${}^{1}_{1.5}ID^{d,7}_{0.25}$
$a=2$			${}^{2}_{0}ID^{d,2}_{0.25}$	${}^{2}_{0.25}ID^{d,3}_{0.25}$	${}^{2}_{0.5}ID^{d,4}_{0.25}$	${}^{2}_{0.75}ID^{d,5}_{0.25}$	${}^{2}_{1}ID^{d,6}_{0.25}$	${}^{2}_{1.25}ID^{d,7}_{0.25}$
$a=3$				${}^{3}_{0}ID^{d,3}_{0.25}$	${}^{3}_{0.25}ID^{d,4}_{0.25}$	${}^{3}_{0.5}ID^{d,5}_{0.25}$	${}^{3}_{0.75}ID^{d,6}_{0.25}$	${}^{3}_{1}ID^{d,7}_{0.25}$
$a=4$					${}^{4}_{0}ID^{d,4}_{0.25}$	${}^{4}_{0.25}ID^{d,5}_{0.25}$	${}^{4}_{0.5}ID^{d,6}_{0.25}$	${}^{4}_{0.75}ID^{d,7}_{0.25}$
$a=5$						${}^{5}_{0}ID^{d,5}_{0.25}$	${}^{5}_{0.25}ID^{d,6}_{0.25}$	${}^{5}_{0.5}ID^{d,7}_{0.25}$

Figure 3. Formal representation of a price matrix

Decision algorithm runs through the year 2021 on a rolling basis and considers a quarter-hourly window with possible trading options for the coming hours (see example in Figure 4 with a 6x8 matrix). As only one decision can be made per product at each time step (every quarter of an hour), this creates a funnel of possible actions. According to these rules, a product, which is about to be delivered, can only be traded once; while the product, which is to be delivered in two hours, can be traded eight times. If a new decision vector is created with the next time step, the revenue $revenue_t$ is recalculated (Expression 3) as a continuous indicator (starting with $revenue_t = 0$).

$$revenue_t = \sum_{s=1}^{S} (I_{a=0,s}^{d,t} * P_{a=0,s}^{d,t} * v * (-1)) + revenue_{t-1} \tag{3}$$

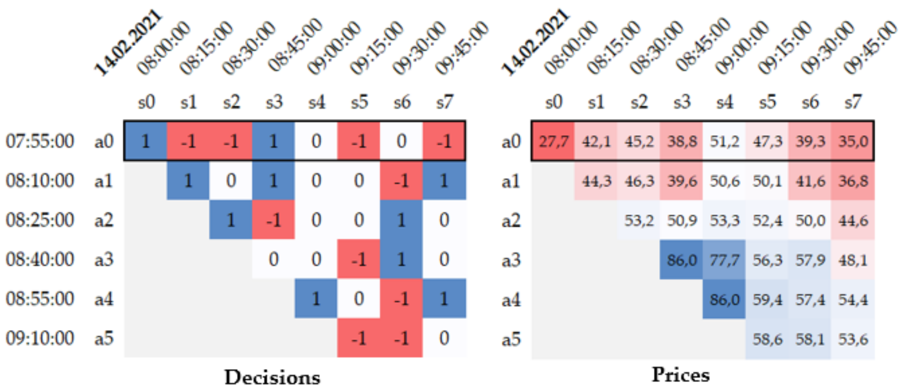

Figure 4. Example: A decision matrix with random decisions and the corresponding prices for the products at decision points a0–a5.

The row of a = 0 represents the trading activities and determines additional revenues, depending on the traded volume (v). Rows a = 1 to a = 5 are the planning horizon. In order to consider battery storage, the algorithm keeps an additional status vector of past decisions and the current battery status. This vector is continuously checked against the new decisions (1,-1,0) so that it can be ensured that the storage and feed-in and feed-out capacity is not exceeded by a new decision combination (Figure 5).

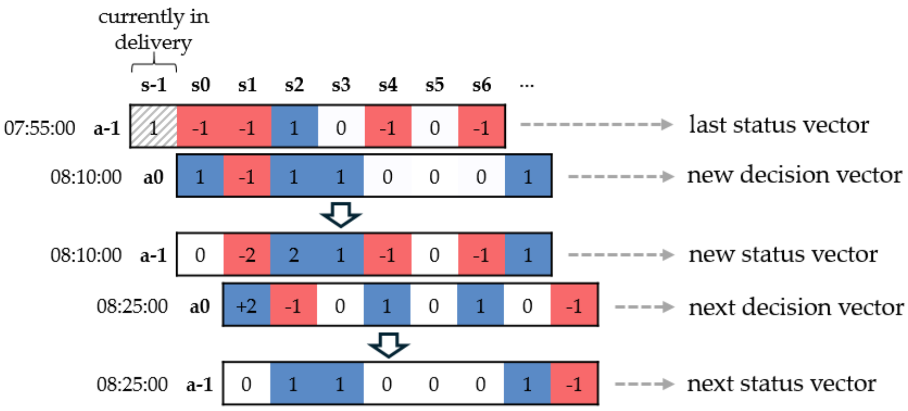

Figure 5. Calculation of status vectors with new decisions to determine the storage status. Decisions are always made at the last possible trading time (5 Min. before delivery).

Whenever there is a change in storage (B), the new storage level is taken into account as the basis for the next decisions (Expression 4).

$$B_{t+1} = B_t + (J_{0,0}^{d,t} * v + J_{0,1}^{d,t-1} * v) \tag{4}$$

4 Model Solution by Genetic Algorithm

Although the original problem is simplified by assumptions and framework conditions, the autonomous search for an optimal solution proves to be difficult due to the large solution space. In the present study, however, a heuristic approach in the form of a genetic algorithm (GA) is pursued, as it can propose feasible solutions within a short period of time and covers a potentially larger solution space through random mutations. Although the GA is, probably, outperformed by other algorithms when it comes to determining the best possible result, we consider it a good benchmark for comparable problems.

A GA is a population-based method whose individuals represent proposed solutions for a complex problem. The procedure is based on the theory of evolution and iteratively runs through a simple multi-phase process to determine a sufficiently good solution for the problem using heuristics. An iteration of a GA takes place after the initialization of the population and typically involves the steps of selection, crossover, mutation, and fitness evaluation. This iterative procedure ensures that better decision combinations are improved generation by generation, while bad or invalid solutions die out.

While a classical GA makes binary decisions, in this study, there are three decision options that lead to buy, sell, or wait. A possible set of decisions is represented by an individual in the population.

Initialization. At the beginning of the run, the individuals are created, and the associated prices are determined. For this purpose, every individual is represented as a matrix $\boldsymbol{J}^{\boldsymbol{d},\boldsymbol{t}}$ that is randomly filled with decisions. Each element in the matrix is an action option for a product (column) at a decision time (row) that is either imminent or still within the planning horizon. To create more feasible solutions, a weighting was applied so that doing nothing occurs twice as often as buying or selling. A mask is used to fill in only those places with a decision that are still feasible at the selected start time. In this and the following runs, we decided on a population size of 25 individuals to form the starting population. To determine the prices, the volume-weighted prices are calculated for each product at quarter-hourly intervals. The historical trading data from EPEX SPOT was used for this purpose. How the prices are calculated can be seen in the article by Narajewski and Ziel [25].

Fitness Function. After initialization (or at the beginning of each iteration), the so-called fitness is determined for every individual of the current population. It is calculated by the fitness function that uses the decision matrix $\boldsymbol{J}^{\boldsymbol{d},\boldsymbol{t}}$ of an individual (i). Unwanted characteristics should lead to a reduction in its fitness via a penalty term. These include exceeding or falling short of:

- *Storage Volume:* This represents the capacity of the battery storage. If it is exceeded or below zero, a penalty term is used. This varies in size:
  - If a decision leads to an exceeded or undercut storage volume for the forthcoming delivery, a very high penalty term is deducted from the fitness. This penalty is considered extremely high because it is a multiple of the charged or discharged volume multiplied by the corresponding price.
  - If a decision leads to an exceeded or undercut storage volume while the delivery is still at least one period (15 minutes) in the future, a moderate penalty term is deducted from the fitness (rather uneconomical). This should reduce the tendency to accumulate commitments over time, leading to large trades just before delivery to meet battery storage limits.
- *Loading Volume*: A fixed amount of energy (v) that can be charged or discharged in one time step t. If more is stored or discharged than the loading volume allows, a moderate penalty term is deducted for the individual. If this happens directly for the next delivery, the penalty term is very high.

The general fitness of an individual (i) without penalty terms can be calculated in the following way (Expression 5) :

$$Fitness_i = \underbrace{\sum_{a=0}^{A}\sum_{s=0}^{S}(J_{a,s}^{d,t} * P_{a,s}^{d,t} * v * (-1))}_{\text{revenue of individual}} + \underbrace{b_i * \frac{1}{S}\sum_{s=0}^{S} P_{0,s}^{d,t}}_{\text{residual value of individual}}, \tag{5}$$

$$while\ b_i = B_t + \sum_{a=0}^{A}\sum_{s=0}^{S}(J_{a,s}^{d,t} * v)$$

The fitness calculation always evaluates the complete individual, including the forecast horizon. The remaining storage of the individual is also considered so that there is no incentive to sell off the storage in favor of a better valuation at the end of the planning horizon.

Selection and Recombination. In recombination, components of the individuals are exchanged with each other. The aim of this procedure is to open a larger search space and to reuse already established structures. To increase the performance generation by generation, a preselection is made for the individuals to be combined. For this purpose, the simple method of fitness-proportional selection is used, which is also known as the "roulette wheel" method [26], [27]. Here, the individuals of the current population are sorted in descending order according to their fitness and, depending on this, are given a probability with which they will be selected for the subsequent recombination. Random individuals are selected for the actual recombination.

The recombination is carried out by means of a submatrix crossover in which individuals exchange their partial solution at a random point. Invalid individuals can arise during the submatrix crossover, so a repair mechanism has to be used.

Mutation. Mutation is another random change process and serves to increase diversity within the population by randomly changing a component of an individual. In concrete terms, this means that after recombination, the decision is changed at a randomly chosen element in the individual decision matrix [28]. Here, too, a repair is subsequently required.

The repair of infeasible individuals is not necessary in a conventional GAs, as all conditions can be mapped via the fitness function. However, this would mean that the algorithm would need more time to converge. Therefore, in our algorithm, the individuals are repaired after recombination and mutation so that only feasible individuals are considered for the next generation. The repair uses the current storage status and the pending decisions to check whether the storage and loading capacity been exceeded for each future delivery time. For this purpose, the column total of the respective individual with the status vector is formed product by product. If the schedule exceeds the loading volume or storage capacity, this is compensated for by additional trades for the corresponding product. In our experiment, we limit the number of genes mutated per individual to one. In, e.g., a 6x8 matrix, this means that a gene has a 1:33 chance of mutating to another state. The mutation rate in this case reflects the rate at which an individual mutates at all (Mutation: yes/no). For larger individuals, two mutations were permitted. In special cases, the algorithm is also permitted to trade more than the permitted maximum volume to comply with the secondary conditions.

Survival Process. To ensure that fitness does not still deteriorate generation after generation, the best individuals are transferred to the next generation without recombination. This process is often called elitism [28], [29] and, in our case, applies to the best two individuals of the current generation. The remaining individuals for the new generation consist of the recombination of the current generation.

Price Variation. Price variation also plays a decisive role in assessing fitness. Since future prices (planning horizon) are not yet fixed and would have to be estimated in a real environment, they are distorted by a factor of uncertainty. This factor indicates the percentage by which each price in the planning horizon can deviate upwards or downwards, thus simulating a simple price forecast. The random prices are determined once for each time step and apply equally to all individuals. This approach is intended to result in the planning horizon changing gradually, requiring repeated responses to possible price changes.

Example: Due to the distorted forecast horizon, it seems profitable for the GA to sell a product at a future point in time. Therefore, it buys that product now at the currently known (real) price, as this is below the forecasted selling price. One time step later, however, the price of the product in question may have fallen. If the GA were to sell the same product now, it would realize a loss. Such situations inevitably occur more frequently with a higher factor of uncertainty and are likely to lead to poorer performance.

5 Results

With the framework conditions described, we would now like to evaluate the extent to which the size of the battery and price uncertainty on real-time markets affect potential profitability. To this end, we are considering different battery storage systems and price uncertainties on the German IDM in several scenarios. The settings for the GA are shown in Table 1

Table 1. Settings for the genetic algorithm (* stays for the agent without storage and ** stays for the largest storage (2MWh) with a longer planning horizon).

Setting	Characteristic
Capacity (in MWh)	0.0, 0.25, 0.5, 1.0, 2.0
Load Volume (in MWh)	0.0*, 0.25
Trade Volume (in MWh)	0.25
Price variation	0.0, 0.1, 0.2, 0.5, 1.0, 2.0
Considered Products per Individual	8, 16**
Planning Horizon per Individual	6, 14**

The number of generations was set to 100, and the mutation probability of 0.9 was selected as the setting for the GA using grid search. By default, a 6x8 matrix was selected for the action matrix, so a product can be traded for the first time two hours before delivery. Although a longer planning horizon is used for the larger battery, it also means that prices are often not available at some trading or planning times. The charging and discharging speed was set at 0.25 MWh for each time period. This is slightly below the average trading volumes per trade for the 15-minute products in 2021, which are shown in Figure 6.

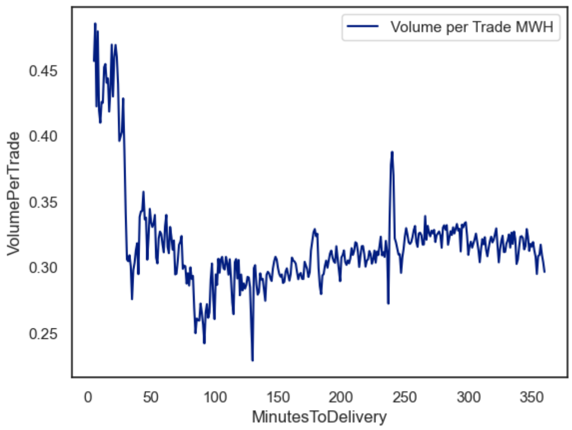

Figure 6. Timeline of average volume per trade for 15-minute products in 2021 from 360 minutes to delivery.

To find out whether the algorithm can generate profits at all, a run with a perfect price forecast (no price variation) was performed for each storage size (Figure 7). While the curves for the algorithms with storage volume show very similar dynamics, the algorithm without a storage unit has a significantly lower earnings level. This clearly shows that the earnings depend considerably on whether a battery is used for trading. It is noticeable here that a significantly stronger increase can be seen from around September, which can be attributed to the higher electricity prices. The charging and discharging volumes were set at 0.25 MWh for each time period. This is slightly below the average trading volumes per trade for the 15-minute products in 2021.

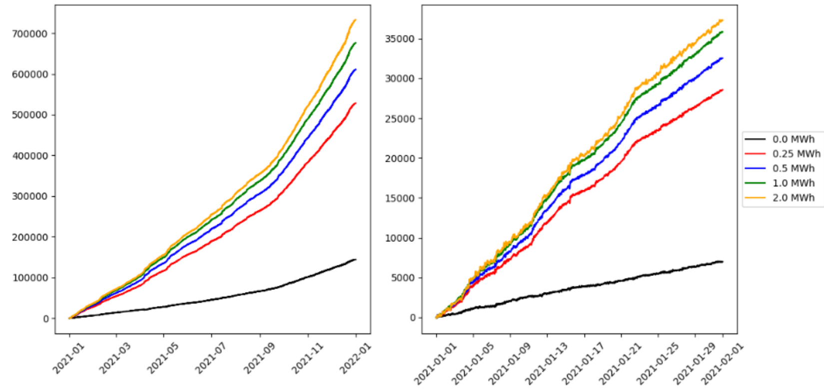

Figure 7. Earnings of agents with perfect price foresight (left – full year view, right – January)

The curves for perfect foresight also suggest that the marginal earnings for the next largest storage unit decrease rapidly at the same charging or discharging speed. While the determined revenue for the agent without storage is € 144 230, this rises to € 528 169 as soon as a battery (0.25 MWh) is available for intermediate storage. The next largest battery (0.5 MWh), on the other hand, generates a relatively lower revenue of € 610 855. The bottleneck here is the limited feed-in and feed-out quantity, which ensures that only one unit (0.25 MWh) can be delivered at a time, particularly at profitable times.

5.1 Detail View

The decisions made by the agents can be seen graphically in Figure 8. The figure illustrates the daily progression of an agent (1 MWh) on a random day, including its buy and sell decisions and its current state of charge. It can also be pointed out here that the storage system is fully charged shortly before peak times and then sold during periods when electricity is more expensive. This behavior can also be seen in the annual average in Figure 9. Here, the storage is at its highest level before the price peaks.

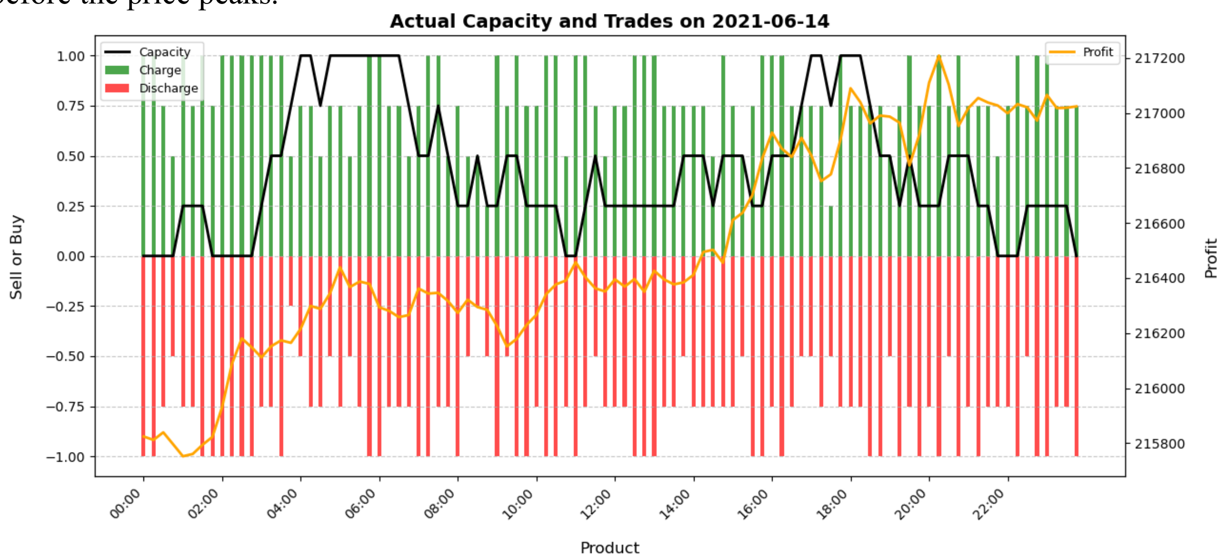

Figure 8. A trading day for a battery with storage (1 MWh)

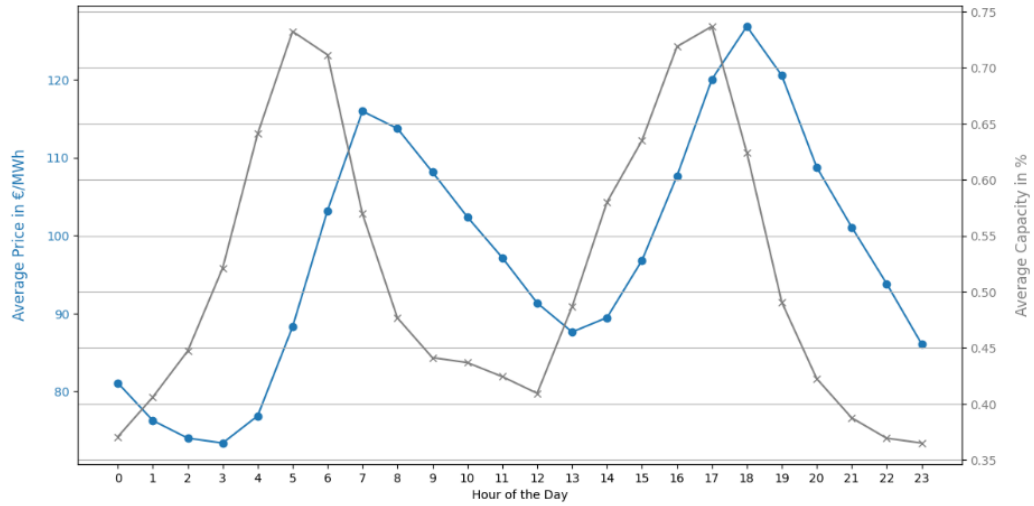

Figure 9. Average price and capacity for each hour of the day

Table 2 presents the revenues and the number of charging cycles for the runs conducted.

Table 2. Results of the GA under perfect price foresight

Capacity	Charging Cycles	⌀ Battery Level	Revenue
0 MWh	0	–	€ 144.230
0.25 MWh	6573	49.6% (0.124)	€ 528.169
0.5 MWh	3849	50.0% (0.250)	€ 610.855
1.0 MWh	2163	51.7% (0.517)	€ 676.445
2.0 MWh	1213	49.9% (0.997)	€ 733.089

5.2 Random Search as Benchmark

Since the benchmark from the previous article [21] did not allow simultaneous transactions between different products, we have instead implemented a method based on a random search approach. The challenging aspect of this method is that it generates invalid solutions that, while theoretically leading to higher sales, are not feasible in practice because they violate storage constraints. Therefore, to obtain only valid solutions, the same repair mechanism as used in GA is applied after random generation of solutions. To avoid disadvantaging Random Search, the unequal distribution of buy, sell, and do nothing decisions used in the initialization of GA is not applied, also making its solution space potentially larger. Additionally, in the context of a random search, the computing time is of significant relevance, as it determines the number of possibilities explored. In this case, the number of tried possibilities is based on the actual computing time of the GA. In our experiment, this number corresponds to a total of 15 000 feasible solution proposals at each iteration. The strategy promising the highest turnover is implemented for each step. Similar to the GA, the traded contracts and battery capacity are also transferred to the next step so that they can be taken into account. This means that the potential of both solutions is essentially the same. The results are presented in Table 3 and Figure 10.

Table 3. Results of the Benchmark under perfect price foresight. (0 – 1.0 MWh)

Capacity	Charging Cycles	⌀ Battery Level	Revenue (diff. to GA)
0 MWh	0	–	€ 125.152 (15%)
0.25 MWh	6882	50.4% (0.126)	€ 449.232 (18%)
0.5 MWh	4056	50.6% (0.253)	€ 499.398 (22%)
1.0 MWh	2162	50,66% (0.507)	€ 530.149 (28%)

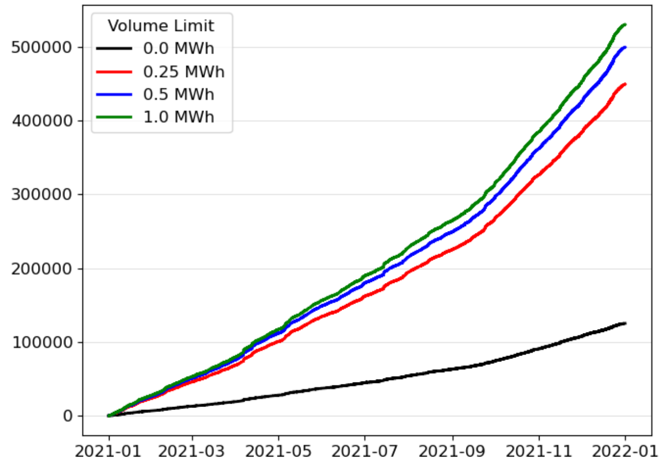

Figure 10. Revenue of Benchmark with perfect price foresight

The benchmark results in Figure 10 are very similar to those obtained by GA (Figure 7). It also turns out that Random Search, as a benchmark method for this particular application, delivers sufficiently competitive results with equal computing time. However, it should be noted that in this case, the GA achieves higher revenues for every storage size. This is also highlighted in Table 3, which shows not only the revenue but also the difference between the GA and Random Search profits in percentage terms. Here, it appears that as the storage size increases, the performance of Random Search decreases. The number of load cycles for 0.25 and 0.5 MWh storage is slightly higher with Random Search, but the average utilization remains the same at around 50%, which indicates that both algorithms are effective strategies for this experiment.

5.3 Price Variation

Since agents with a planning horizon have always had perfect price foresight, we now assign an uncertainty factor to the prices in the planning horizon. This approach is intended to more closely reflect actual market conditions and simulate price forecasts, such as those used in the form of path forecasts [30]. This factor is a random number with evenly distributed probability and ensures that the price changes by a maximum percentage up or down with varying confidence. For this purpose, the following values for price distortion were assumed in combination with different BESS sizes:

Capacity (in MWh): 0, 0.25, 0.5, 1

Uncertainty (α): 0.0, 0.1, 0.2, 0.5, 1.0, 2.0

Depending on its severity, the uncertainty factor can cause the price to be significantly distorted (Expression 6).

$$\hat{p}_{a,s}^{d,t} = p_{a,s}^{d,t} * (1 + \epsilon), \epsilon \sim U(-\alpha, \alpha) \quad (6)$$

All prices in a planning horizon of the price matrix $P_{a,s}^{d,t}$ a = 1,…, A are affected by the price distortion. Here, too, the year 2021 was simulated for all combinations, assuming all other conditions remained the same. Since the GA also takes the planning horizon into account through its fitness function, we expected price uncertainties to have a significant impact on profitability.

Examining the results of this experiment, it is therefore not surprising that, in addition to battery capacity, price differences also have a significant impact on revenue. This can be seen in Figure **11** and Figure 12.

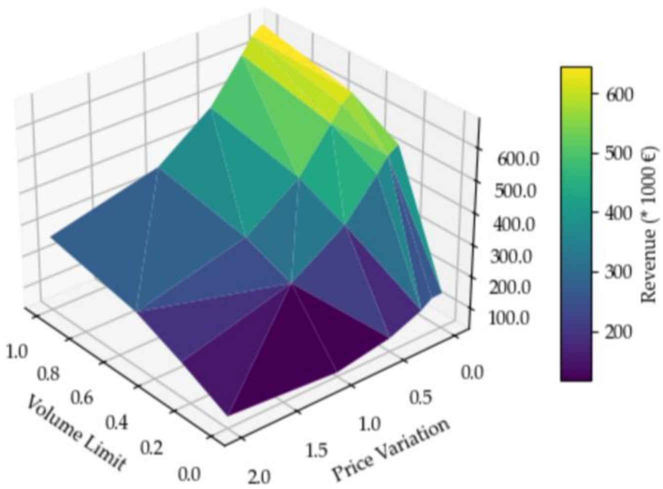

Figure 11. Revenue per storage capacity and price variation

The greater the uncertainty, the lower the simulated revenue. However, this does not appear to happen to the same extent. For instance, with a battery size of 0.5 MWh and perfect price foresight, the profit changes from € 610 855 to € 587 301 at α = 0.1, which corresponds to a change of ~4%. The next step to α = 0.2 with the same battery size yields only € 540 813, which corresponds to approximately 8%. This drop in profit decreases again with higher price uncertainties. More detailed data on the runs can be found in the Appendix. However, the correlation between profit and price uncertainty and the correlation between profit and battery capacity do not seem to be comparable to the same extent.

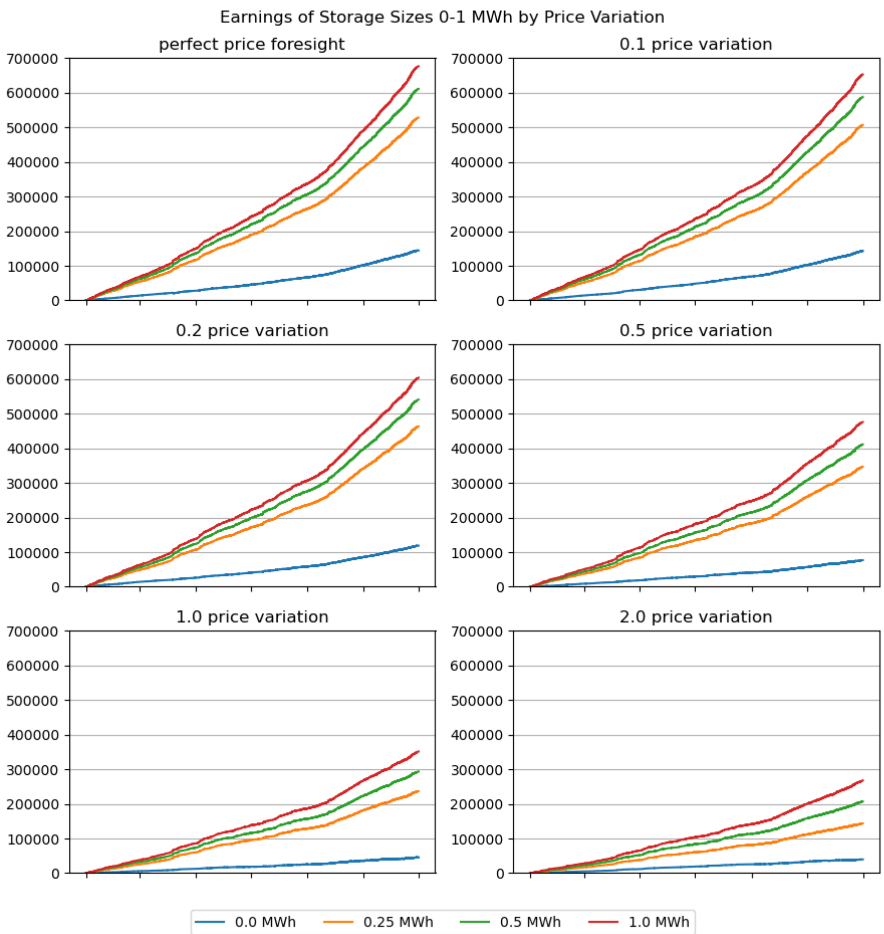

Figure 12. Revenues from different price variations according to battery storage

It is now interesting to find out which of the two influencing factors, battery capacity or price uncertainty, has a greater impact on revenues. In order to compare the influence of the two variables approximately, we performed a simple linear regression on the various revenues at the end of the year (Expression 7).

$$\boldsymbol{Revenue = \beta_0 + \beta_1 * vlimit + \beta_2 * \alpha + \epsilon} \tag{7}$$

The coefficient for battery storage capacity (*vlimit*) is 2.991×10^5, which shows a direct positive correlation with profitability. In contrast, the coefficient for price uncertainty (α) has a negative value of -1.633×10^5. This confirms that increasing uncertainty in market prices reduces profitability. Here, it can be argued that battery storage capacity has a stronger positive influence on profitability than the negative influence of price uncertainty. This can be seen from the fact that the absolute value of the coefficient for vlimit is greater than that for *pvar*, which indicates a stronger marginal effect.

Table 4. Linear Regression for Volume Limit and Price Variation

Variable	Coeff.	Std. error	t	p-value	95% conf. interval
Constant	299 106.17	39 353.50	7.010	0.000	[2.17×10^5, 3.81×10^5]
Volume_limit	362 519.30	59 203.48	6.123	0.000	[2.39×10^5, 4.86×10^5]
Price Variation (α)	-163 344.06	31 523.74	-5.182	0.001	[-2.29×10^5, -9.78×10^4]

With an R^2 of 0.731, the model explains a large part of the variance in profitability. The F-statistic is 32.17 with a p-value below 0.001.

5.4 Test with Systematic Forecast Errors

In the previous section, we examined the extent to which price uncertainties can influence profitability due to price variation. It would now be interesting to know to what extent the GA in use reacts to underestimates and overestimates, e.g., due to biased forecast models. In this section, we will systematically underestimate and overestimate the previously evenly distributed price uncertainty to examine the effects this has on profitability and storage utilization. For this purpose, the underestimation is described in Expression 8.

$$\hat{p}_{a,s}^{d,t} = p_{a,s}^{d,t} * (1 + \epsilon), \epsilon \sim U(-\alpha, 0) \tag{8}$$

Analogue to this is overestimation, shown in Expression 9.

$$\hat{p}_{a,s}^{d,t} = p_{a,s}^{d,t} * (1 + \epsilon), \epsilon \sim U(0, \alpha) \tag{9}$$

Once again, uncertainty is applied exclusively to the planning horizon. We expect price uncertainty to directly impact the decision maker's profit. For instance, in the overestimation scenario, the algorithm may favor buying at the current point in time because future prices tend to be higher, offering the prospect of future sales. However, this would result in the storage facility being filled excessively often. This could lead to situations where the storage facility is full at favorable moments, meaning that it can no longer make lucrative purchases. The reverse applies in the case of underestimation.

It is already foreseeable that this distortion of the planning horizon is likely to have the greatest impact on the test runs with real battery storage. We have therefore used the following values for this run:

Capacity (in MWh): 0.25, 0.5, 1

Uncertainty (α): 0.1, 0.2, 0.5, 1.0

The results of the experiment are represented in Figure 13. The upper plot shows the already known profits for storage facilities with capacities of 0.25, 0.5, and 1 MWh with the different price variations. The orange dots indicate the average storage utilization over the entire year 2021.

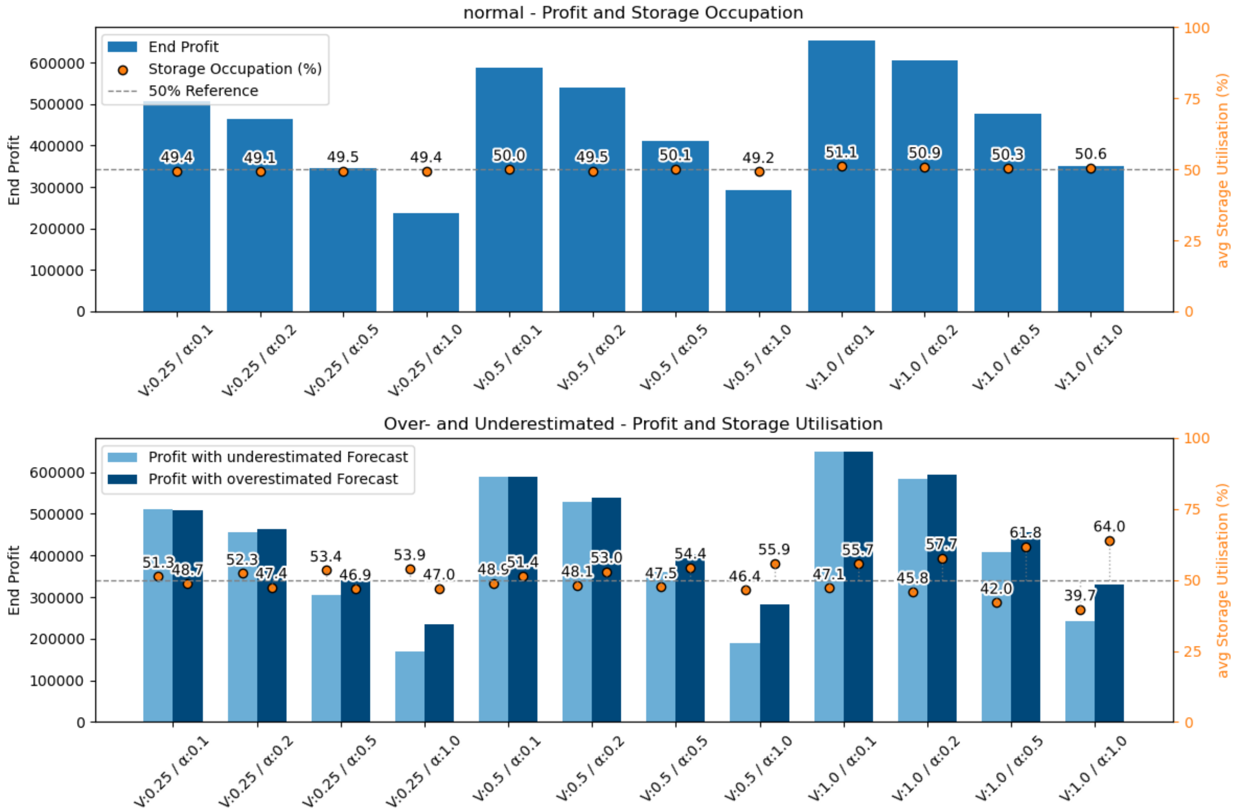

Figure 13. Profit and storage utilization with under- and overestimated forecasts (V: battery size, α: price variance).

The lower plot shows the systematic price variation for different storage sizes. Here, significant differences can be seen between underestimation and overestimation. As expected, greater price variation leads to overuse of storage in the overestimation scenario, while the storage remains more often empty in the case of systematic underestimation. Despite the same ratio in price variation, the difference in the under- and overuse of storage varies. For instance, the average state of charge for the 1 MWh battery with a price deviation of α = 1.0 is 64% in the overestimation scenario and 39.7% in the underestimation scenario. All other settings being equal, the decision maker also earns significantly more in the high overestimation scenario (α = 1.0) than in the high underestimation scenario.

The most obvious explanation for these two circumstances is that the decision maker in the underestimation scenario had fewer opportunities to act in 2021. The number of charging cycles confirms this. For instance, the GA in the overestimation scenario (α = 1.0, 1 MWh) required 1428.5 charging cycles, while in the underestimation scenario, only 1255.5 charging cycles were performed during the same period. In comparison, the scenario without underestimation or overestimation resulted in 2311 charging cycles. In this regard, it can be concluded that unilateral price distortion, regardless of the direction, leads to poorer overall performance. This is particularly noteworthy because the balanced variation (U(-α, α)) has, in total, a greater range of uncertainty than the two distorted scenarios.

6 Discussion

As can be inferred from the results of the experiment, it is possible to obtain significant positive revenues by utilizing the GA. By varying the battery size, we can draw conclusions about storage utilization and marginal revenues. The jump from no storage to a small storage (0.25 MWh) leads to a strong revenue increase of about 266% (perfect price prediction), which underlines the fundamental importance of storage capacity for arbitrage trades. However, the results show decreasing marginal returns with increasing battery capacity. The increase in revenue to 0.50 MWh is around 16%, while the jump to 1 MWh only yields just under 7% more. Theoretically, the revenue could be increased by larger feed-in and feed-out sizes and a proportionally larger storage facility. However, a single player would quickly reach the natural limits of the market by simply stacking up the storage volume [15].

What we have now been able to conclude by expanding the scope is that price uncertainty is also an influential leverage for arbitrage trading. However, the effect of this uncertainty on revenue is measurably lower than the effect of battery size. This circumstance, therefore, has direct implications when it comes to where the focus of investments should lie in practice. In particular, when considering investing more in better forecasting algorithms or larger battery storage systems, the cost-benefit ratio should always be kept in mind. It should also be mentioned here that our maximum price spreads of up to 200% deviate significantly from standard state-of-the-art forecasts.

In Section 5.4, we were also able to show how systematic distortions in forecasts affect battery usage and; therefore, the profit of the proposed algorithm. The result was that both underestimating and overestimating real prices led to sharp declines in profits. This is due to the fact that, depending on the scenario, the algorithm is no longer able to maintain balanced battery storage. As a result, it is unable to react in critical situations.

We had to limit our experiment with certain restrictions. These included the discretization of the problem and the associated formation of volume-weighted prices. To simplify the optimization problem, our experiment also assumes no cost structures for re-amortization, trading costs, efficiency losses, or spreads. Instead, we assume a liquid market in which we can always buy and sell at the average price. Other researchers, such as Bertrand and Papavasiliou [12] or Schaurecker et al [14], have demonstrated a much more complex experimental setup, but without the implementation of a planning window considering future prices. In our opinion, the latter point also deserves more attention, as there has been significant progress in this area of research. For instance, Marcjasz, Unijewski et al. [31] showed that they were able to beat the naïve approach when forecasting intraday prices – in other words, they were able to provide significantly better price forecasts than the last known price. Similar to the results of Schaurecker et al. [14], we were able to determine that batteries with fast and small storage units appear to be more profitable in terms of dimensioning. It must also be said that Schaurecker et al. used significantly larger batteries for their experiment. However, it remains to be seen whether intraday-only battery trading can really pay off in the long term. The ever-falling prices for BESS currently speak in favor of battery trading [20], [32]. In addition, it is expected that electricity prices in Europe will remain at a high level in the medium to long term [33]. Both trends could favor the use of BESS.

7 Conclusion

The objective of this article was to use an experimental approach to examine seizing of battery storages in the continuous German intraday market. For this purpose, a GA was implemented that trades at discrete time intervals and takes a planning horizon into account. This should allow identification of arbitrage options, taking into account a storage limit. The first finding here was that the size of the battery storage is a significant driver of profitability, but the marginal profit decreases rapidly. Additionally, we demonstrated that the algorithm could achieve positive intraday turnover without utilizing storage even once. However, this is only possible with accurate price forecasting techniques. We also demonstrated that small, fast charging/discharging storage units perform best on the intraday market. Using a battery can be associated with considerable earnings, but the marginal benefit decreases rapidly for each next larger battery. In addition, we were able to show that although forecast errors do influence the algorithm's turnover, in this application case, battery size is likely to have a greater impact on profitability. Overestimating and underestimating prices result in not using the battery at a balanced ratio and thus being unable to trade in critical situations.

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Appendix

Supplementary Material

Table A1. Systematic testing with under- and overestimation

Capacity	α	Variant	End Profit	⌀ Battery Level	Charging Cycles
0.25	0.1	normal	€ 506 517.87	0.49	6503.00
		underestimated	€ 510 164.29	0.51	6364.00
		overestimated	€ 509 421.81	0.49	6533.00
	0.2	normal	€ 463 213.09	0.49	6761.00
		underestimated	€ 456 058.11	0.52	6102.00
		overestimated	€ 462 950.59	0.48	6225.00
	0.5	normal	€ 346 532.33	0.49	7000.00
		underestimated	€ 303 849.36	0.53	5356.00
		overestimated	€ 341 330.55	0.47	5616.00
	1.0	normal	€ 236 804.90	0.49	7032.00
		underestimated	€ 169 768.15	0.54	4686.00
		overestimated	€ 235 837.38	0.47	4950.00
0.50	0.1	normal	€ 587 301.22	0.50	3939.50
		underestimated	€ 588 814.95	0.49	3696.00
		overestimated	€ 589 087.76	0.51	3764.50
	0.2	normal	€ 540 812.55	0.49	3968.00
		underestimated	€ 527 507.83	0.48	3504.00
		overestimated	€ 538 275.70	0.53	3616.00
	0.5	normal	€ 411 192.88	0.50	4163.00
		underestimated	€ 360 391.45	0.48	2919.00
		overestimated	€ 402 713.33	0.54	3117.50
	1.0	normal	€ 293 550.63	0.49	4149.50
		underestimated	€ 189 961.95	0.46	2277.00
		overestimated	€ 282 793.99	0.56	2630.00
1.00	0.1	normal	€ 652 606.94	0.51	2168.50
		underestimated	€ 649 815.23	0.47	2075.75
		overestimated	€ 649 506.96	0.56	2110.00
	0.2	normal	€ 604 114.14	0.51	2210.75
		underestimated	€ 583 946.96	0.46	1962.75
		overestimated	€ 595 170.71	0.58	1982.00
	0.5	normal	€ 475 808.04	0.50	2293.75
		underestimated	€ 407 932.23	0.42	1595.25
		overestimated	€ 455 237.79	0.62	1733.75
	1.0	normal	€ 351 362.86	0.51	2311.00
		underestimated	€ 243 324.90	0.40	1255.50
		overestimated	€ 330 124.61	0.64	1428.50

Table A2. Overall price variation scenario

MWh / α	0	0.1	0.2	0.5	1	2
0	€ 144 256	€ 142 761	€ 118 721	€ 76 886	€ 58 148	€ 39 630
0.25	€ 528 177	€ 506 521	€ 463 227	€ 346 537	€ 236 810	€ 143 522
0.5	€ 610 855	€ 587 301	€ 540 813	€ 411 193	€ 293 574	€ 206 999
1	€ 676 446	€ 652 622	€ 604 117	€ 475 808	€ 351 387	€ 267 336