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Profitability of batteries in day-ahead and intraday electricity markets: Assessment of operation strategies with endogenous prices

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ABSTRACT

Batteries can support future electricity systems by assisting price arbitrage in electricity markets, enhancing self-consumption, and providing ancillary services. Determining the profitability of price arbitrage , i.e. charge at low prices and discharge at high prices., requires evaluating the strategy that is used to benefit from future price fluctuations, and considering its impact on prices. This study examines battery profitability based on price arbitrage in day-ahead and intraday auction markets, where both temporal price differences within markets and price differences between markets are exploited. This is done with an electricity-market model, calibrated on historical Dutch bid-curve data, which estimates the impact of battery bids on market equilibria. We compare profits under perfect foresight with a strategy where the storage operator has perfect foresight of prices but ignores the own effect on prices, and two simpler historical-data-based strategies. It appears that the latter type of simpler strategies can result in profitable operations in case of small battery capacity, and that most profits can be made in the intraday market. However, when battery capacity increases, profitability declines, especially in the intraday market, due to lower market volumes. Increased battery capacity also calls for more advanced operation strategies, as historical price patterns may no longer predict future prices accurately. Even in a year with high price volatility as in 2023, with perfect foresight of prices and 60% lower battery costs, no more than 15% of Dutch households with solar panels can profitably invest in home batteries.

1. Introduction

To reduce the absolute levels of carbon emissions, as well as to increase the generation capacity in order to facilitate electrification of industry, transport and residential sector, governments are promoting the development and use of renewable energy sources like solar Photovoltaic (PV) and wind electricity. As the electricity production of solar panels and wind turbines depends, unlike fossil-fuel power plants, on meteorological conditions, the latter type of plants might still remain necessary for resource adequacy. In order to make electricity systems carbon neutral, therefore, the attention is increasingly going to alternative technologies that provide the flexibility to transfer electricity within time. One of such technologies that currently receives a lot of attention is batteries. This electricity storage technology allows electricity to be converted into chemical energy during charging. This energy is stored, and can later be converted back into electricity when the battery discharges. Compared to other electricity storage technologies, batteries offer relatively low energy losses in the short term, making them suitable for supporting grid stability and improving the integration of renewable energy sources (Topalović et al., 2023). In fact, battery storage is currently the fastest-growing clean energy storage technology. By 2023, total battery storage capacity in the energy sector exceeded 2,400 GWh, marking a fourfold increase since 2020 (IEA, 2024).

The amount of batteries and their role in future energy systems will depend on their expected profitability. In electricity markets, this profitability depends on the value of energy arbitrage, where batteries are charged at low prices and discharged when prices are higher (Elshurafa, 2020), optimizing own energy consumption, capacity mechanisms or provision of ancillary services, or benefiting from additional income through support mechanisms (Bonkile and Ramadesigan, 2022; Komorowska and Olczak, 2024). In European electricity systems, day-ahead markets offer energy arbitrage opportunities. In these markets, organized as auctions, participants submit price-volume bids, indicating the amount of electricity they are willing to buy or sell and for what price, for each hour of the following day. The market closes around noon the day before the delivery period, and shortly after market closure the hourly Market Clearing Prices (MCPs, here-after electricity prices) are published. Due to constant changes in factors such as available generation capacity, forecasted demand, and fuel prices, electricity prices fluctuate over time. Operators of flexibility sources,

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Table 1
Literature overview of studies investigating the profitability of batteries using energy arbitrage.

Reference	Price effect		Market		Data	
	Ex.	En.	DA	ID	Region	Period
Arcos-Vargas et al. (2020)	X		X		Spain	August 2016 -July 2017
Komorowska et al. (2022)	X		X		Poland	2016–2020
Núñez et al. (2022)	X		X		24 EU countries	2019
Mercier et al. (2023)	X		X		31 European countries	2000/2007–2021
Komorowska and Olczak (2024)	X		X		22 EU countries	2016–2022
Topalović et al. (2024)	X		X		Austria, Bosnia and Herzegovina	2011–2019
Mohamed et al. (2024)	X		X		France	2021
Kazempour et al. (2009)	X		X		Spain	NA
Hu et al. (2022)	X		X		7 EU countries	2019–2021
Andreotti et al. (2024)	X		X		Italy	April 2023 - March 2024
Metz and Saraiva (2018)	X		X	X	Germany	2011/2015–2016
Arteaga and Zareipour (2019)	X	X	X		USA	NA
Antweiler (2021)		X	X		USA	2014–2017
Barbry et al. (2019)		X	X		USA	2016
Sioshansi et al. (2009)	X	X	X		USA	2002–2007
Shafiee et al. (2016)		X	X		USA	2010–2014
Van Cappellen et al. (2022)		X	X		Market model	2020, 2025, 2030
Koolen et al. (2023)		X	X		Market model	2030, 2050
This study	X	X	X	X	Netherlands	2006–2023

Notes: Price effect: prices are considered exogenous (Ex.), or endogenous (En.). Market: Day-ahead (DA) and/or Intraday auction (ID). The studies of Andreotti et al. (2024), Arteaga and Zareipour (2019), Van Cappellen et al. (2022) do not consider the intraday auction market, but do analyse the profitability of batteries in other markets, such as the intraday continuous market, frequency regulation service, spinning reserve, and non-spinning reserve.

like batteries, can take advantage of these price fluctuations over time, a strategy known as temporal energy arbitrage.

Every day after the day-ahead electricity market has closed, market participants might want to adjust their portfolios when more accurate information about electricity supply and demand becomes available. Adapting the portfolio can be done by trading on intraday auction markets. These markets operate similarly to the day-ahead market, but trade electricity in 15 min intervals and they close a few hours after the day-ahead market closes, introducing additional flexibility to market participants. This additional flexibility is valuable in an electricity system with so-called program responsibility and high shares of renewable electricity generation. The former means that market participants have financial incentives to act in real time according to their trading decisions. Regarding the latter, it appears that volumes traded on the intraday-auctions auctions are strongly correlated with the intermittence of solar generation (Metz and Saraiva, 2018).[1]

Similar to the day-ahead markets, intraday prices fluctuate over time, offering additional temporal energy arbitrage opportunities to flexibility providers like batteries. On top of these two sources of temporal arbitrage within markets, since the day-ahead and intraday markets run in parallel, battery-storage operators can benefit from price differences between the two markets, by buying electricity in the market with the lower price and selling in the market with the higher price. This type of arbitrage, from now on referred to as between-markets arbitrage[2] can be purely financial, as it might not require the battery-storage operator to physically deliver electricity, but rather to manage offsetting position across markets, and can enhance the profitability of battery-storage systems (Metz and Saraiva, 2018).

Existing studies regarding the profitability of batteries using energy arbitrage often focus solely on temporal energy arbitrage in one market, and/or assume batteries to be price-takers, i.e., they ignore the potential effects of the operations of batteries on prices. Table 1 provides an overview of related studies, highlighting whether prices are treated as endogenous or exogenous, the markets in which the battery operators operate, and the time periods and countries covered by the data. In the remainder of this section, references will be made to the papers mentioned in the table.

Almost all studies in Table 1 focus solely on temporal energy arbitrage in one market. This may underestimate the profitability of batteries, as between-markets arbitrage opportunities might be significant as well. Moreover, the price-taker assumption might be valid in current energy systems, where batteries play a minor role. However, as more and more batteries are installed[3] this assumption might no longer hold (Lamp and Samano, 2022; Rangarajan et al., 2023). An economic analysis of battery profitability, therefore, needs to take into account the effects of battery-storage operators on electricity prices. This can be done via an electricity market model, where the electricity price is endogenously determined.

This study sheds light on the profitability of batteries that use both between-markets and temporal energy arbitrage and operate in day-ahead and intraday auction electricity markets as they exist in Europe. First, we focus on the current situation in the Dutch electricity system, where the installed battery capacity is limited, and calculate the profitability of battery systems under the assumption of battery-storage operators being price-takers, i.e., we ignore the effect of battery-storage operators on electricity prices. As batteries have to participate in the auctions to benefit from price fluctuations, they have to decide on charging and discharging before the electricity prices are known. Therefore, we evaluate and compare three different control strategies, which determine the timing and quantity of electricity trading electricity, and differ in the extent to which knowledge of future prices is required.

Then, we relax the assumption of exogenous electricity prices, and calculate the profitability of price-maker batteries in the current Dutch

[1] In this study, we use data on the Dutch day-ahead and intraday auction markets between 2006 and 2023. In the Netherlands, the intraday auction, known as IDA1 was introduced in October 15, 2020. This intraday auction market closes at 15:00 CET (Central European Time) for electricity delivery for all 96 quarters (24 h) of the next day. Since 13 June 2024, two additional intraday auctions, IDA2 and IDA3, exist. The IDA2 market closes at 22:00 CET, for delivery for all 96 quarters of the next day. The IDA3 market closes at 10:00 the following day, for the last 12 h of that day.

[2] In the literature, this type of arbitrage is known as spatial arbitrage as energy is (virtually) transferred between markets. However, as the arbitrage does not take place between different locations, but rather between different markets, we prefer to use the term between-markets arbitrage.

[3] In September 2024, the Dutch electricity market, for instance, contains 216 MW of operating batteries, 168 MW is under construction, and 1244 MW is in the final permitting process (Ventolines, 2024). In 2030, the Dutch TSO Tennet expects 4000–5000 MW to be operational (TenneT, 2023).

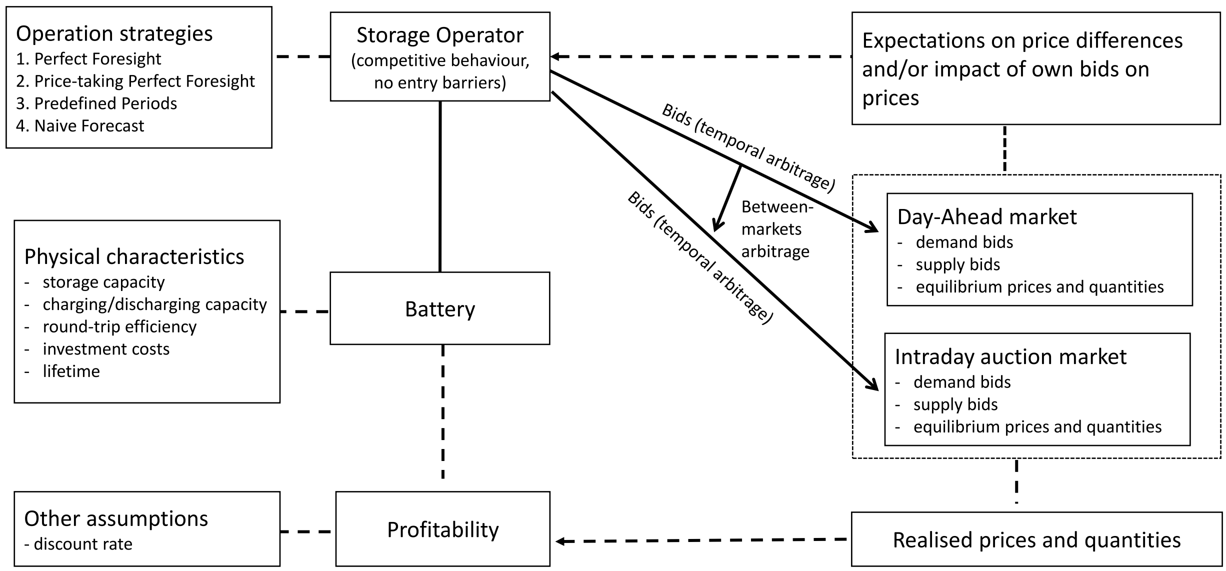

Fig. 1. Overview of research framework.

electricity system for different battery capacities installed. We do this using an electricity market model based on an extensive dataset of the European Power Exchange (EPEX), containing market clearing prices, quantities, and bids of the Dutch markets in 2023. Contrary to other market models, such as METIS (Koolen et al., 2023), ATLAS (Little et al., 2024), ASSUME (Harder et al., 2023), AMIRIS (Schimeczek et al., 2023), EMLab (Chappin et al., 2017), and PowerACE (Fraunholz et al., 2021), we use bidding data as model input, and do thus not model the entire merit order. This is because, on the short term, there is only a weak relation between the full merit order based on all power plants in an electricity market and the market bids. A bid in the day-ahead or intraday electricity market does not necessarily correspond to a specific power plant: for example, power producers can make use of the synergies within a portfolio (e.g. virtual power plants), and retailers can resell electricity previously bought in surplus on forward and future markets (Mahler, 2022). By directly using bidding data, our approach gives thus a more realistic view of the short-term electricity markets and, hence, also of the effects of battery operations on market outcomes. Other day-ahead electricity market models, like the European Electricity Market Model EMMA (Hirth et al., 2021) and the Enertile model (Fraunhofer, 2024) assume perfectly price-inelastic electricity demand. By explicitly modelling bids, our approach is more flexible and better reflects the underlying market structures of day-ahead and intraday electricity markets. In addition, by directly using bidding data, our analysis requires less assumptions. For example, we do not have to assume that electricity demand can be predicted accurately, (as assumed by Barbry et al., 2019) that there is a relationship between prices and generating load (Sioshansi et al., 2009), or how many batteries can be placed to keep investments profitable (Van Cappellen et al., 2022). To the best of our knowledge, we are the first to consider battery storage using combined trading in the day-ahead and intraday electricity markets with endogenous prices.

Our results show how battery-storage operators can make profits through energy arbitrage. In current electricity markets, where batteries play a minor role, we show that operational profits are highest for temporal arbitrage in the intraday market, and that between-markets arbitrage opportunities are limited. Moreover, we show that even with simple storage strategies based on historically observed patterns, substantial revenues can be made. However, when more batteries are installed, arbitrage opportunities diminish, especially in the intraday auction market. This results in increased benefits of between-markets arbitrage, as price differences between markets increase. Furthermore, in case of high installed battery capacity, making a profit with energy arbitrage becomes more difficult without perfect foresight of future prices, as the charging activities of battery operators alter price patterns.

This paper is structured as follows. Section 2 presents the research methodology, and Section 3 describes the data used in the analysis. In Section 4, we present the results, and Section 5 provides concluding remarks.

2. Methodology

We investigate the profitability of a battery that is operated by a profit-maximizing storage operator, active in competitive day-ahead and intraday electricity markets. We compare the revenue obtained from the electricity injected in the grid minus the costs of buying electricity from the grid and the investment costs. The battery operator can operate on the day-ahead market, the intraday market, or sequentially on both. We evaluate four control strategies, which determine the timing and volumes of electricity purchases and sales. One strategy assumes perfect foresight of future prices and its own effect on prices, providing a theoretical upperbound of operational profits. The second strategy also assumes perfect foresight of prices, but ignores the own effect of market operations on prices. The other two strategies use historical data to determine charging and discharging decisions, and give conservative estimates of operational profits. We provide a visual representation of the research framework in Fig. 1.

In the remainder of this section, we first discuss our methodology for the different strategies for price-taker battery-storage operators, i.e., we assume that the battery size is limited such that the operations of the storage operator do not affect prices. This price-taker approach is relatively simple as prices are treated as exogenous, but becomes invalid when the installed battery capacity increases. Therefore, we also consider the situation where more batteries are operating in the electricity markets and the effects of the battery-storage operators on prices are taken into account. From a modelling perspective, we will only describe a battery-storage operator that operates first in the day-ahead market, and then in the intraday market. We remark the changes required to obtain the methodology of a battery-storage operator that only operates in one of the two markets thereafter. For the notation, we follow the approach of Metz and Saraiva (2018). We work in discrete time steps of 15 min, as the intraday auction works with time steps of this duration. As the actions and prices in the day-ahead market apply for a period of 1 h, we change these durations accordingly.

2.1. Profitability of batteries under price-taker strategies

2.1.1. Perfect Foresight strategy

For this strategy, we assume that the storage operator has perfect knowledge of future electricity price in the near future. Specifically, electricity prices of the next T^{PF} time periods are known. Given this knowledge of future prices, the storage operator makes decisions at periods $t \in \{1, 1+T^{\mathrm{PF}}, 1+2T^{\mathrm{PF}}, \dots\}$, when the storage operator decides how much electricity to buy and/or sell in the following T^{PF} periods. The knowledge of future prices allows the storage operator to perfectly determine its optimal (dis)charging strategy. Therefore, the revenue of this strategy provides an upperbound for the operational profits of the storage operator.

Stage 1: day-ahead electricity market. At period $t \in \{1, 1+T^{\mathrm{PF}}, 1+2T^{\mathrm{PF}}, \dots\}$, the storage operator first decides the operations in the day-ahead electricity market for the following T^{PF} periods, by maximizing

$$\max_{q^b_{\mathrm{DA}}(t),\dots,q^b_{\mathrm{DA}}(t+T^{\mathrm{PF}}-1),q^s_{\mathrm{DA}}(t),\dots,q^s_{\mathrm{DA}}(t+T^{\mathrm{PF}}-1)} \sum_{i=t}^{t+T^{\mathrm{PF}}-1} p_{\mathrm{DA}}(i)(q^s_{\mathrm{DA}}(i)-q^b_{\mathrm{DA}}(i)) - H^{\mathrm{DA}}(q^s_{\mathrm{DA}}(i)+q^b_{\mathrm{DA}}(i)). \tag{1}$$

The cash flows of charging and discharging in period i consist of the day-ahead electricity price ($p_{\mathrm{DA}}(i)$) multiplied by the net amount of electricity sold ($q^s_{\mathrm{DA}}(i)-q^b_{\mathrm{DA}}(i)$). However, with the assumption of no operating costs, arbitrary small price differentials would be exploited by the storage operator. This could be problematic, as batteries have limited lifespans, which are negatively related to intensity of utilization. Frequent battery use can therefore quickly deplete a battery's operational life, preventing the battery operator to benefit from potentially lucrative arbitrage opportunities in its remaining lifespan. Conversely, if the dispatch is too conservative, calendar aging will dominate, also resulting in missed opportunities for profitable arbitrage. Therefore, the additional hurdle term H^{DA} is introduced as revenue threshold, and reflects the opportunity costs of using the battery (Metz and Saraiva, 2018).

In addition, the operations of the storage operator are constrained:

$$0 \le q^s_{\mathrm{DA}}(i) \le \min\{C^D, S(i)\eta^D/4\}, \tag{2a}$$

$$0 \le q^b_{\mathrm{DA}}(i) \le \min\{C^C, (S^M - S(i))/4\eta^C\}, \tag{2b}$$

for $i = t, t+1, \dots, t+T^{PF}-1$. The amount of electricity that can be sold ($q^s_{\mathrm{DA}}(i)$) is non-negative, and is constrained by the discharging capacity (C^D) and the storage level ($S(i)$), corrected by the discharging efficiency (η^D). Similarly, the amount of electricity that can be bought ($q^s_{\mathrm{DA}}(i)$) is non-negative, and constrained by the charging capacity (C^C) and the remaining storage level ($S^M - S(i)$), corrected by the charging efficiency η^C. The storage level is updated via

$$S(1) = S^0, \tag{3a}$$

$$S(i) = S(i-1) + q^b_{\mathrm{DA}}(i-1)\eta^C - q^s_{\mathrm{DA}}(i-1)/\eta^D, \qquad i > 1. \tag{3b}$$

Moreover, as we work in time steps of 15 min, and the day-ahead market operates on an hourly basis, the actions satisfy

$$q^s_{\mathrm{DA}}(j) = q^s_{\mathrm{DA}}(j+1) = q^s_{\mathrm{DA}}(j+2) = q^s_{\mathrm{DA}}(j+3), \tag{4a}$$

$$q^b_{\mathrm{DA}}(j) = q^b_{\mathrm{DA}}(j+1) = q^b_{\mathrm{DA}}(j+2) = q^b_{\mathrm{DA}}(j+3), \tag{4b}$$

for $j = t, t+4, t+8, \dots, t+T^{PF}-5$, to ensure that the power is constant during every hour, so equal in all four 15-min intervals.[4]

We denote the profit-maximizing actions by $q^b_{\mathrm{DA}*}(t), \dots, q^b_{\mathrm{DA}*}(t+T^{\mathrm{PF}}-1), q^s_{\mathrm{DA}*}(t), \dots, q^s_{\mathrm{DA}*}(t+T^{\mathrm{PF}}-1)$.

Stage 2: intraday electricity market. After the closure of the day-ahead market, the storage operator decides upon its operations in the intraday electricity market, given the already determined profit-maximizing actions in the day-ahead market. The corresponding optimization problem is given by:

$$\max_{q^b_{\mathrm{ID}}(t),\dots,q^b_{\mathrm{ID}}(t+T^{\mathrm{PF}}-1),q^s_{\mathrm{ID}}(t),\dots,q^s_{\mathrm{ID}}(t+T^{\mathrm{PF}}-1)} \sum_{i=t}^{t+T^{\mathrm{PF}}-1} p_{\mathrm{ID}}(i)(q^s_{\mathrm{ID}}(i)-q^b_{\mathrm{ID}}(i)) - H^{\mathrm{ID}}(q^s_{\mathrm{ID}}(i)+q^b_{\mathrm{ID}}(i)), \tag{5}$$

subject to

$$0 \le q^{out}(i) \le \min\{C^D, S(i)\cdot\eta^D\}, \tag{6a}$$

$$0 \le q^{in}(i) \le \min\{C^C, (S^M - S(i))/\eta^C\}, \tag{6b}$$

for $i = t, t+1, \dots, t+T^{PF}-1$, where

$$S(1) = S^0, \tag{7a}$$

$$S(i) = S(i-1) + q^{in}(i-1)\eta^C - q^{out}(i-1)/\eta^D, \qquad i > 1, \tag{7b}$$

and

$$q^{in}(i) - q^{out}(i) = q^b_{\mathrm{ID}}(i) - q^s_{\mathrm{ID}}(i) + q^b_{\mathrm{DA}*}(i) - q^s_{\mathrm{DA}*}(i), \tag{8}$$

for $i = t, t+1, \dots, t+T^{PF}-1$. This optimization problem is similar to the one in the day-ahead market in Eqs. (1)–(4b). However, as the storage operator has to take into account its actions on the day-ahead market, the battery-storage operations are now limited via the total amounts of electricity charged (q^{in}) and discharged (q^{out}), which depend on both the operations in the day-ahead and the operations in the intraday auction market via Eq. (8). We denote the profit-maximizing actions by $q^b_{\mathrm{ID}*}(t), \dots, q^b_{\mathrm{ID}*}(t+T^{\mathrm{PF}}-1), q^s_{\mathrm{ID}*}(t), \dots, q^s_{\mathrm{ID}*}(t+T^{\mathrm{PF}}-1)$.

Updating storage level. After the decisions in the day-ahead and intraday market are determined, the storage level at the end of the T^{PF} periods is given by

$$S(t+T^{PF}) = S(t) + \sum_{i}^{t+T^{PF}-1} q^{in}(i)\eta^C - q^{out}(i)/\eta^D. \tag{9}$$

This storage level is used as input for the optimization problem at the next decision period.

2.1.2. Price-taker Perfect Foresight

Under the Price-taker Perfect Foresight strategy, the storage operator perfectly predicts future electricity prices that would result if the storage operator did not participate in the electricity market. Under the price-taker assumption, this leads to the same optimization problem as for the Perfect Foresight strategy, and both strategies result in the same operational strategy and profitability. However, when the effects of the storage operator are taken into account, as is done in Section 2.2, electricity prices might change. Under the Perfect Foresight strategy, we assume that these effects are known by the storage operator, and taken into account when operational profits are maximized. Under the Price-taker Perfect Foresight strategy these effects are ignored, the storage operator behaves as a price-taker. As such, when the effects of battery storage operations on prices are taken into account, and more batteries are being installed, the storage decisions and operational profits might differ between the two strategies.

For both variants, the storage operator maximizes the optimization problem as described in Eqs. (1)–(9). The two storage variants are implemented differently into the electricity market model, which we discuss in Section 2.2.

2.1.3. Predefined Periods strategy

The second strategy is based on the analysis of Komorowska et al. (2022), who shows that in the Polish day-ahead market, daily minimum and maximum prices usually occur in the same hours, regardless of the year analysed. As such, a simplified charge and discharge strategy over the same periods could lead to positive operational profits. By defining these periods using historical data, this strategy can be used without the knowledge of future prices. The profits found with this

[4] For simplicity, we assume that T^{PF} is a multiple of 4.

strategy can be seen as conservative, which might be increased by including predictions of future prices. The strategy defines four sets of periods: $\mathcal{T}^B_{\text{DA}}, \mathcal{T}^B_{\text{ID}}, \mathcal{T}^S_{\text{DA}}, \mathcal{T}^S_{\text{ID}} \subseteq \mathcal{T}$, which describe during which periods electricity is bought ($\mathcal{T}^B_{\text{DA}}, \mathcal{T}^B_{\text{ID}}$) and sold ($\mathcal{T}^S_{\text{DA}}, \mathcal{T}^S_{\text{ID}}$), while taking into account charging and storage capacities. Following Komorowska et al. (2022), we use sets that adhere to a daily cycle, such that electricity is bought or sold in the same periods (quarters) of each day:

$$\mathcal{T}^B_{\text{DA}} = \left\{ x + 96(d-1) | x \in \mathcal{T}^{B,\text{day}}_{\text{DA}}, d \in \{1,2,\dots,365\} \right\}, \tag{10a}$$

$$\mathcal{T}^B_{\text{ID}} = \left\{ x + 96(d-1) | x \in \mathcal{T}^{B,\text{day}}_{\text{ID}}, d \in \{1,2,\dots,365\} \right\}, \tag{10b}$$

$$\mathcal{T}^S_{\text{DA}} = \left\{ x + 96(d-1) | x \in \mathcal{T}^{S,\text{day}}_{\text{DA}}, d \in \{1,2,\dots,365\} \right\}, \tag{10c}$$

$$\mathcal{T}^S_{\text{ID}} = \left\{ x + 96(d-1) | x \in \mathcal{T}^{S,\text{day}}_{\text{ID}}, d \in \{1,2,\dots,365\} \right\}, \tag{10d}$$

where $\mathcal{T}^{B,\text{day}}_{\text{DA}}, \mathcal{T}^{B,\text{day}}_{\text{ID}}, \mathcal{T}^{S,\text{day}}_{\text{DA}}$ and $\mathcal{T}^{S,\text{day}}_{\text{ID}}$ contain the quarters (from the 96 quarters within a day) designated for electricity purchase and sale respectively, and d represents the day of the year.[5]

Stage 1: day-ahead electricity market. Every hour, at period $t \in \{1, 5, \dots, T-3\}$, the storage operator first determines the amounts of electricity to be bought or sold in the day-ahead market. If t is part of the predefined sets $\mathcal{T}^B_{\text{DA}}$ or $\mathcal{T}^S_{\text{DA}}$, the storage operator buys or sells as much electricity as possible, given charging constraints and available storage capacity:

$$q^b_{\text{DA}}(t) = \begin{cases} \min\{C^C, (S^M - S(t))/4\eta^C\} & \text{if } t \in \mathcal{T}^B_{\text{DA}}, \\ 0 & \text{otherwise,} \end{cases} \tag{11a}$$

$$q^s_{\text{DA}}(t) = \begin{cases} \min\{C^D, S(t)\eta^D/4\} & \text{if } t \in \mathcal{T}^S_{\text{DA}}, \\ 0 & \text{otherwise.} \end{cases} \tag{11b}$$

As the day-ahead market operates per hour, we have that

$$q^b_{\text{DA}}(t) = q^b_{\text{DA}}(t+1) = q^b_{\text{DA}}(t+2) = q^b_{\text{DA}}(t+3), \tag{12a}$$

$$q^s_{\text{DA}}(t) = q^s_{\text{DA}}(t+1) = q^s_{\text{DA}}(t+2) = q^s_{\text{DA}}(t+3). \tag{12b}$$

The storage level $S(t)$ is equal to zero for $t = 1$, and is updated after the operations on the intraday market are determined.

Stage 2: intraday electricity market. Next, the storage operator determines how much electricity to buy or sell in the intraday electricity market. This is done in a way similar to Eq. (11a) and (11b). However, the decisions in the intraday market are now also constrained by the operations in the day-ahead market. The mathematical formulation of this can be found in Appendix C.

2.1.4. Naive Forecast

Finally, we consider a control strategy inspired by Sioshansi et al. (2009), which predicts future electricity prices by assuming they remain consistent with recent prices. This strategy uses the same optimization structure of the Perfect Foresight strategy, and $T^{\text{NF,f}}$ defines how many periods are used in the optimization problem, and sets the decision periods $t \in \{1, 1+T^{\text{NF,f}}, 1+2T^{\text{NF,f}}, \dots\}$. However, instead of using future prices, the storage operator now uses historical price data of $T^{\text{NF,b}} \geq T^{\text{NF,f}}$ periods ago. Consequently, at period t, the storage operator maximizes its operations based on price data from the preceding periods $t-T^{\text{NF,b}}, t-T^{\text{NF,b}}+1, \dots, t-T^{\text{NF,b}}+T^{\text{NF,f}}-1$. The actions that were optimal for these historical prices are then implemented for future prices. Similar to the Predefined Periods strategy, this strategy provides a conservative estimate of the profitability of batteries.

2.2. Profitability of batteries under price-maker strategies

Next, we relax the assumption of the electricity prices being exogenous. To do so, we modify the short-term partial equilibrium model of Veenstra and Mulder (2024) to mimic the auctions of the day-ahead and intraday electricity markets and take into account the effect of battery-storage operators on these markets. In this model, the electricity price is not an exogenous variable, but the market-clearing price of the market that matches supply with demand.

2.2.1. Electricity-market model

We model an electricity market of sellers and buyers of electricity who submit bids. These bids consist of a price and a quantity, which we use to determine the amount of electricity traded by the market participants. We distinguish between market participants that want to buy electricity, market participants that want to sell electricity. In line with previous research (Ziel and Steinert, 2016), we consider so-called simple bids only, and do not consider more complicated bidding products like block bids and complex bids (EPEX, 2024).[6]

Buying bid: At period t, in market $m \in \{\text{DA}, \text{ID}\}$, an electricity buyer with bid $i \in \mathcal{B}_m(t)$ has a willingness-to-pay $\text{WTP}^i_m(t)$ for an amount of electricity $Q^{b,i}_m(t)$. We determine the quantity that can be bought ($q^{b,i}_m(t)$), given the market price and willingness to pay, in the following optimization problem:

$$\max_{0 \leq q^{b,i}_m(t) \leq Q^{b,i}_m(t)} \left(\text{WTP}^i_m(t) - p_m(t) \right) q^{b,i}_m(t), \tag{13}$$

As such, electricity is bought only when the electricity price is smaller than the willingness-to-pay.

Selling bid: An electricity seller in period t, market $m \in \{\text{DA}, \text{ID}\}$, with bid $j \in \mathcal{S}_m(t)$ faces a marginal cost $\text{MC}^j_m(t)$ for supplying $Q^{s,j}_m(t)$ units of electricity. We determine the quantity that can be sold ($q^{s,j}_m(t)$), given the market price and the marginal cost, in the following optimization problem:

$$\max_{0 \leq q^{s,j}_m(t) \leq Q^{s,j}_m(t)} \left(p_m(t) - \text{MC}^j_m(t) \right) q^{s,j}_m(t), \tag{14}$$

Hence, electricity is sold only when the electricity price exceeds the marginal costs of production.

Market-clearing price: Combining all optimization problems of all buyers and sellers, the electricity price $p_m(t)$ is such that total demand equals total supply:

$$\sum_{i \in \mathcal{B}_m(t)} q^{b,i}_m(t) = \sum_{j \in \mathcal{S}_m(t)} q^{s,j}_m(t). \tag{15}$$

This market-clearing price can be directly derived from the bids as the intersection of the so-called demand and supply price curves (Ziel and Steinert, 2016), which order and aggregate the bids. However, when batteries are added to the system, this approach becomes more complicated, as market outcomes might change.[7] Therefore, we follow the approach of Veenstra and Mulder (2024) and set up a mixed complementarity problem based on the Karush–Kuhn–Tucker (KKT) conditions for all market participants with market-clearing conditions (Gabriel et al., 2012). We solve the mixed complementarity problem with the General Algebraic Modelling Systems (GAMS) software. The model is solved for each market separately, reflecting the separation of these markets in real-life.

2.2.2. Storage strategies

For the price-maker analysis, we consider the same strategies as described in Section 2.1. For the Perfect Foresight strategy, we set up the KKT conditions of the optimization problem of the storage operator (Eqs. (1)–(4b) in the day-ahead market, Eqs. (5)–(8) in the intraday

[5] In leap years, $d \in \{1, 2, \dots, 365, 366\}$.

[6] This would make the analysis more complex, without necessarily providing more insights. As we only consider simple bids, the market-clearing processes in different periods are independent of each other, such that we can solve our model per period.

[7] This is especially relevant for the Perfect Foresight strategy, where the price curves, and the effect of the storage operator on these curves are assumed to be known.

market), and add these conditions to the corresponding mixed complementarity problem. We also change the market-clearing constraint in Eq. (15) to

$$\sum_{i\in\mathcal{B}_m(t)} q_m^{b,i}(t) + q_m^b(t) = \sum_{j\in\mathcal{S}_m(t)} q_m^{s,j}(t) + q_m^s(t), \tag{16}$$

where we add the actions of the storage operator $(q_m^b(t), q_m^s(t))$ to the actions that result from the initial bids. As the actions of the storage operator depend on its previous and future actions, the mixed complementarity problems are now solved for T^{PF} periods simultaneously.

For the Predefined Periods strategy, the Naive Forecast Strategy, and the Price-taker Perfect Foresight strategy, we model the buying and selling bids of the storage operator in the same way as we model the other bids in our electricity market model. Specifically, the buying bid of the storage operator is modelled as in Eq. (13), with a willingness-to-pay equal to $\bar{p}^m$, and the quantity offered is specified by the strategy. Similarly, the selling bid of a storage operator is modelled as in Eq. (14), with a marginal cost equal to $\underline{p}^m$. For the Price-taking Perfect Foresight strategy, this implies that we first solve the optimization problem described in Section 2.1.1 with exogenous prices. The actions that follow from these optimization problem are then added to the electricity market model. Hence, in all these three strategies, the bids are treated as exogenous variables in the electricity market model.

When the storage operator does not use the Perfect Foresight strategy to determine its charging and discharging decisions, it lacks knowledge of other bids. Therefore, it is possible that its bid may not be (fully) fulfilled, which may cause problems for future bids. If a buy bid is not (fully) satisfied, we assume that the storage operator goes to another market, and buys the remaining electricity for a price of $\bar{p}^m$. Similarly, when a selling is bid is not satisfied, the storage operator sells the remaining electricity for a price of $\underline{p}^m$.

2.3. Comparing strategies

In order to compare the different strategies, we calculate operational profits Π :

$$\Pi = \sum_{t=1}^{T} \pi_t = \sum_{t=1}^{T} p_{\mathrm{DA}}(t)(q_{\mathrm{DA}}^s(t) - q_{\mathrm{DA}}^b(t)) + p_{\mathrm{ID}}(t)(q_{\mathrm{ID}}^s(t) - q_{\mathrm{ID}}^b(t)), \tag{17}$$

consisting of revenues obtained in the day-ahead market and the revenues obtained in the intraday market. To evaluate the business case of investing in batteries, we calculate the current value of investing in a battery via the Net Present Value (NPV). In calculating the NPV, the investment costs are weighted against the cashflows in other periods, which are discounted with the discount rate r to control for the time value of money and financial risks related to the investment. A positive NPV indicates that the projected earnings from an investment in a battery exceed all costs, indicating that it is expected to be more than profitable (Mulder, 2023). We extend the approach of Metz and Saraiva (2018), such that

$$\mathrm{NPV} = -(K^S + K^C)\cdot(1-\gamma)\cdot \max\left(\frac{\mathrm{NC}}{L^{\mathrm{CYC}}}, \frac{T}{L^{\mathrm{CAL}}}\right) + \sum_{t=1}^{T} \frac{\pi_t}{(1+r)^{\frac{t}{T}}}, \tag{18}$$

where NC, the number of cycles, is given by

$$\mathrm{NC} = \sum_{t}^{T} \frac{(q_{\mathrm{DA}}^b(t) + q_{\mathrm{ID}}^b(t))\eta^C + (q_{\mathrm{DA}}^s(t) + q_{\mathrm{ID}}^s(t))/\eta_D}{2S^M}. \tag{19}$$

In our analysis, the battery lifetime is not entirely simulated. Therefore, only a fraction of the investment cost, consisting of the storage costs per MWh (K^S) and capacity costs per MW (K^C), scaled by the cost reduction rate γ, is used to determine the NPV. This fraction of the investment cost is either determined by the calendric lifetime limit ($\frac{T}{L^{\mathrm{CAL}}}$), or the operational limit ($\frac{\mathrm{NC}}{L^{\mathrm{CYC}}}$).

For the Perfect foresight strategy, Price-taker Perfect Foresight strategy, and Naive Forecast strategy, the hurdles h^{DA} and h^{ID} play an important role in determining the activity of the battery, and which limit is reached first. A small hurdle leads to an increased battery use, such that the operational limit is reached earlier. When the hurdle increases, the battery is used less often, such that at some point the lifetime limit becomes binding.

2.4. Operating on one market

When battery operators participate in both the day-ahead and intraday auction markets, the potential for between-markets energy arbitrage can increase operational profits. However, the added complexity of managing operations on two markets may not always be advantageous. To explore this, we also assess the profitability of batteries that are limited to operating in just one of the markets. When the battery operator exclusively participates in the day-ahead market, we set $q_{\mathrm{ID}}^b(t) = 0$ and $q_{\mathrm{ID}}^s(t) = 0$ for $t = 1, \dots, T$. Conversely, for operations solely in the intraday market, we set $q_{\mathrm{DA}}^b(t) = 0$ and $q_{\mathrm{DA}}^s(t) = 0$ for $t = 1, \dots, T$.

3. Assumptions and data

3.1. General assumptions

Throughout our analysis, we consider a battery-storage system with a round-trip efficiency of 85% (Cole et al., 2021). We use equal charging and discharging efficiencies, yielding an approximate value of 0.92 ($\sqrt{0.85}$). For battery costs, we use 238,000 Euro/MWh for storage capacity and 212,400 Euro/MW for charging and discharging capacity, following Hu et al. (2022). We set the calendric lifetime and cycle lifetime at 15 years and 5000 cycles respectively, with a discount factor of 7%, in line with previous studies such as Metz and Saraiva (2018).

In our analysis of a price-taker battery-storage operator, we focus on a battery with a charging and discharging capacity of 1 MW. Research by Mercier et al. (2023) indicates that storage durations exceeding four to six hours offer diminishing marginal value. Hence, we consider a 4-hour battery with a storage capacity of 4 MWh. As the cost for battery storage is expected to decrease (Orangi et al., 2024), we also consider scenarios with lower costs. Specifically, for the price-taker analysis, we calculate the cost reduction rate γ that is required to make the NPV of investing in a battery non-negative.

For the analysis of price-maker battery-storage operators, we also consider 4-hour batteries, but with various storage size capacities. For the Perfect Foresight strategy, we compare the performance metrics of a battery with an installed storage capacity of 4 MWh, 1000 MWh and 2000 MWh. Similar to the price-taker analysis, we also calculate the cost reduction rate γ that is required to make the NPV of investing in a battery non-negative. For the Predefined Periods strategy, the Naive Forecast strategy, and the Price-taking Perfect Foresight strategy, we take this approach one step further. For cost reduction rates γ equal to 0%, 30%, and 60%, we calculate the storage capacity of batteries such that the NPV of investing in battery equals zero. This capacity reflects, under the assumption of no entry barriers, such as grid congestion, and competitive behaviour, the break-even level of storage capacity in the market (Dixit and Pindyck, 1994).[8]

The evaluation of the different strategies is carried out annually, so that $T = 35{,}040$ (i.e., 8760 hours × 4 quarters per hour). Using historical prices, we calculate nominal annual operational profits, and calculate the NPV of investing in a battery under the assumption that the electricity-price patterns of a historical year remain the same in each of the future years during the lifetime of the battery. In all cases, the battery is empty at the beginning of the year.

[8] We do not calculate these break-even levels for the Perfect Foresight Strategy, as this requires us to search for both the hurdle that maximizes operational profits, and the break-even level of capacity, which would require multiple days of model calculations. Moreover, the break-even levels are more relevant for the other strategies, as these strategies can actually be implemented.

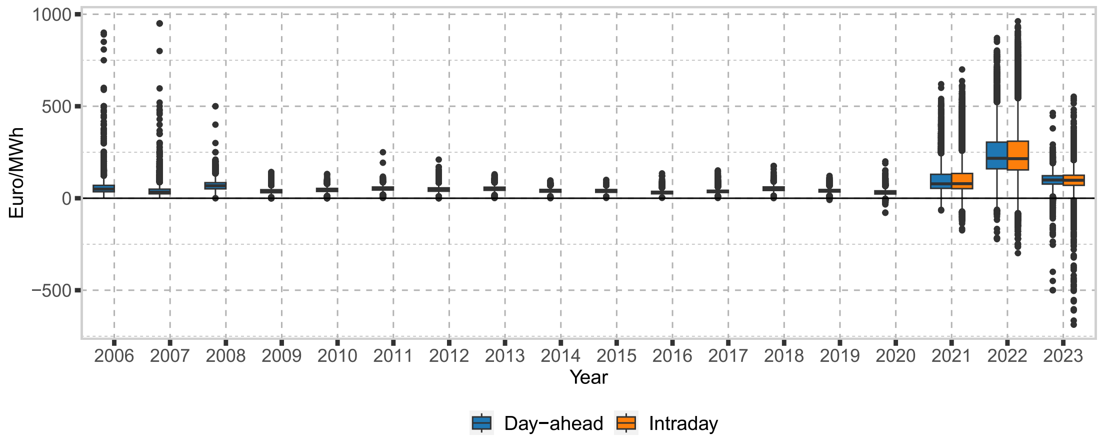

Fig. 2. Boxplots of the Dutch day-ahead and Intraday electricity price for the periods 2006–2023 (day-ahead) and 2021–2023 (intraday auction), in Euro/MWh.
Notes: The central box spans from the first quartile to the third quartile, capturing the middle 50% of data points, which is known as the interquartile range (IQR). Inside this box, a line marks the median, showing the midpoint of the distribution. Vertical lines extend from the box and represent the data range to up to 1.5 times the IQR above the third quartile and below the first quartile. Any points that fall outside these lines are plotted individually as potential outliers.

3.2. Data on electricity prices

To estimate the profitability of a price-taker battery-storage operator, we use data on hourly day-ahead and intraday electricity prices resulting from the Dutch wholesale market from EPEX (EPEX, 2024). For the day-ahead market, we use data over the period 2006–2023. The Dutch intraday auction was founded in the end of 2020, such that we use data for 2021–2023. For illustration purposes, Fig. 2 shows boxplots of the Dutch electricity prices, per year and market. In the figure, we observe relatively low day-ahead electricity prices in 2006–2020. In 2006–2008, some extreme prices were observed, due to scarcity of generation capacity (Mulder et al., 2008). From 2021 onwards, average day-ahead electricity prices increased, while also the volatility increased. This can be attributed to changes in the European day-ahead markets, driven by increasing shares of variable renewable sources and rising prices of gas and coal in the global markets (Cevik and Ninomiya, 2023; Zakeri et al., 2023). To show how the increasing share of renewables and the level of gas prices relate to electricity prices, we show scatterplots of these variables in Figs. D.1 and D.2 in Appendix D. The intraday prices usually fluctuate around the day-ahead electricity prices, and show a higher volatility.

3.3. Data on bidding curves

To analyse the potential impacts of an energy storage facility, we use data from the EPEX on all-NEMO[9] market bids on the Dutch day-ahead and intraday auction market in 2023. During this period, 50.6 TWh of electricity was traded on the day-ahead auction market, and 0.33 TWh was traded on the intraday auction electricity market. The total load in the Netherlands in 2023 was equal to 116 TWh (CLO, 2024). However, these numbers cannot be directly compared, as electricity that is, for instance, traded on the day-ahead market can also be traded on intraday markets. The data consists of hourly (day-ahead) or quarterly (intraday) lists specifying the buying and selling price–quantity bids. These bids are used as input for the electricity market model specified in Section 2. We assume static supply and demand curves, and we do not consider any alterations to the bids of other market participants or market coupling resulting from the actions of the storage operator.

In the EPEX, the market clearing price is determined by the EUPHEMIA algorithm, where it is assumed that the relation of two different bid price and quantity combinations of one market participant is linear (Ziel and Steinert, 2016). As our data does not contain information on which bids belong to which participant, there is sometimes a small difference between our market clearing price and the true market price. Specifically, for the day-ahead electricity price in 2023, in 32% of all hours our market clearing price matches exactly, and in 88% of all hours the difference is smaller than 1 Euro/MWh. For the intraday market in 2023, in 94% of all hours our market clearing price matches exactly, and in 96% of all hours the difference is smaller than 1 Euro/MWh.

3.4. Storage strategies

For the strategy-specific parameters and hurdles, we adopt the following approach. In the case of the Perfect Foresight strategy and Price-taker Perfect Foresight strategy, we incorporate daily volatility (Billé et al., 2023), setting $T^{\mathrm{PF}} = 96$. This assumption allows the storage operator to accurately forecast electricity prices for the following day. We also explored larger values of T^{PF}, extending up to 2016 (21 days). However, under the price-taker assumption, this extension of the forecast period did not lead to significantly higher profitability. Specifically, the annual operational profits obtained with $T^{\mathrm{PF}} = 96$ were at most 6% lower than those achieved with the horizon that maximized operational profits. To balance between short-term high operational profits on the one hand, and the number of cycles on the other hand, we use a grid search to determine the hurdle rate that maximizes the NPV of battery usage over its lifetime. These (annual) hurdles can be found in Appendix B. Generally, the optimal hurdle increases with the price volatility.

For the Predefined Periods strategy, the sets of periods per day that are designated for electricity purchase ($\mathcal{T}_{\mathrm{DA}}^{B,\mathrm{day}}, \mathcal{T}_{\mathrm{ID}}^{B,\mathrm{day}}$) and sale ($\mathcal{T}_{\mathrm{DA}}^{S,\mathrm{day}}, \mathcal{T}_{\mathrm{ID}}^{S,\mathrm{day}}$) are based on historical price data. For $m \in \{\mathrm{DA}, \mathrm{ID}\}$, we define n^{m} as the number of periods (quarters) in $\mathcal{T}_{\mathrm{m}}^{B,\mathrm{day}}$ and $\mathcal{T}_{\mathrm{m}}^{S,\mathrm{day}}$. We let $\mathcal{T}_{\mathrm{m}}^{B,\mathrm{day}}$ and $\mathcal{T}_{\mathrm{m}}^{S,\mathrm{day}}$ contain an equal number of periods, such that all electricity bought is sold within the same day. Then, as a day contains 96 quarters and in a given quarter, electricity is either bought, sold, or no electricity is traded, we have that $1 \leq n^{\mathrm{m}} \leq 48$. For a given $1 \leq n^{\mathrm{m}} \leq 48$, we determine the periods in the sets by analysing the electricity prices of the previous year. For each day in that preceding year, we first determine during which quarter the lowest and highest prices were observed. For $\mathcal{T}_{\mathrm{m}}^{B,\mathrm{day}}$, we rank the quarters based on the number of times the lowest price was observed in that quarter. Then,

[9] The bids of all Nominated Electricity Market Operators (NEMOs) are considered, i.e., all exchanges active in Dutch market area are included. Moreover, the EPEX formatted curves are shifted in order for the curves to cross at the Market Clearing Prices.

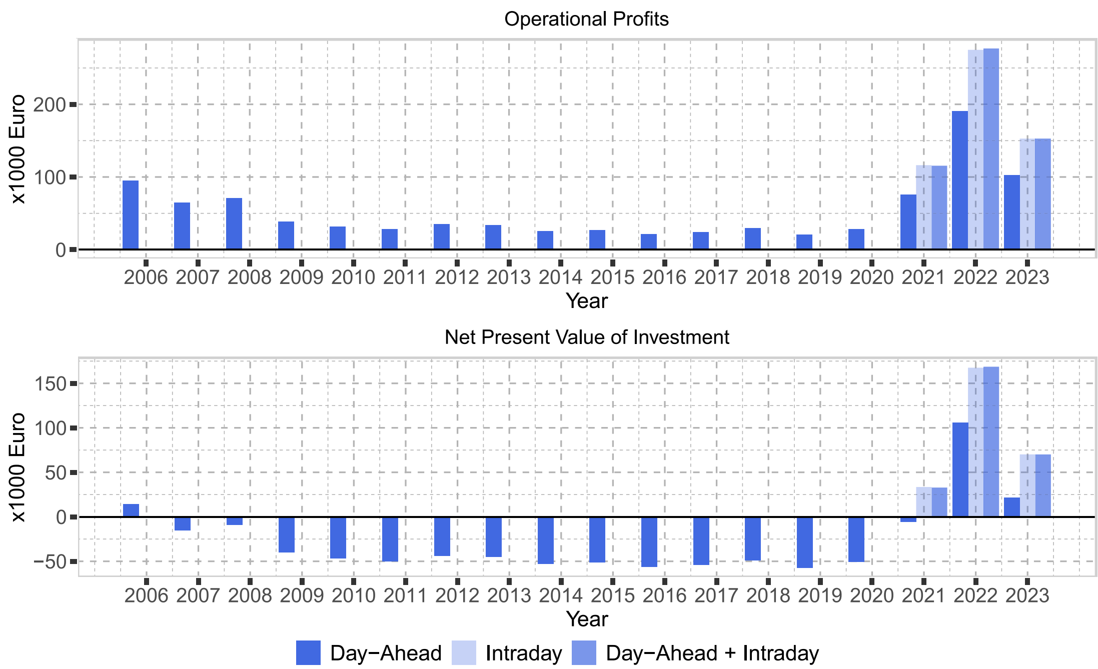

Fig. 3. Annual operational profits and Net Present Value (1000 euros) of a price-taker battery-storage operator operating in the Dutch day-ahead (2006–2023) and/or intraday markets (2022–2023) with a storage capacity of 4 MWh, charging capacity of 1 MW, discharging capacity of 1 MW, Perfect Foresight strategy, per market, without cost reduction. Notes: Operational Profits and Net Present Value are in nominal terms. For year y, the Net Present Value is calculated under the assumption that the electricity-price patterns of year y remain the same in each of the future years during the lifetime of the battery. The cost-reduction parameter γ is equal to zero.

$\mathcal{T}_{\mathrm{m}}^{B,\mathrm{day}}$ contains the top n^{m} quarters of this ranked list. Similarly, we rank the quarters based on the number of times the highest price was observed in that quarter, and let $\mathcal{T}_{\mathrm{m}}^{S,\mathrm{day}}$ contain the top n^{m} quarters of this ranked list. We then calculate the operational profits that would have been obtained with the Predefined Periods strategy using $\mathcal{T}_{\mathrm{m}}^{B,\mathrm{day}}$ and $\mathcal{T}_{\mathrm{m}}^{S,\mathrm{day}}$ (each containing n^{m} quarters). We repeat this procedure for all $1 \le n^{\mathrm{m}} \le 48$, and select n^{m} that result in the highest NPV. We use the same sets for both the price-taker and price-maker analysis. For every year, these sets can be found in Appendix B.

For the Naive Forecast strategy, we take $T^{\mathrm{NF,b}} = 672$ and $T^{\mathrm{NF,f}} = 96$. Hence, the storage operator looks back at the data from previous week to determine its strategy, and optimizes its operations one day at a time. As such, we capture potential weekly patterns (Sioshansi et al., 2009). Similar to the Predefined Periods strategy, we use the hurdle that maximizes the NPV in the previous year, and use the same hurdles for the price-taker and price-maker analysis.

For the Predefined Periods- and Naive Forecast strategy, the bidding prices are set to the minimum and maximum observed electricity prices of 2022:

$$\underline{p}^{\mathrm{DA}} = -500, \bar{p}^{\mathrm{DA}} = 463.77, \underline{p}^{\mathrm{ID}} = -298.5, \bar{p}^{\mathrm{ID}} = 962. \tag{20}$$

These prices also apply when additional electricity is traded if bids are not fulfilled.

4. Results

This section presents and discusses the research results. First, the operational profits of price-taker operators of batteries in the Dutch electricity markets are analysed and compared across different years and control strategies. Second, we analyse the impact of using batteries for arbitrage purposes on the Dutch day-ahead and intraday electricity markets, and the corresponding effect on operational profits and NPV.

4.1. Profitability of price-taker battery

4.1.1. Perfect Foresight strategy

To assess the economic viability of batteries based on price arbitrage in historical Dutch day-ahead and intraday markets, we show the annual operational profits and corresponding NPV of investing in batteries in the different markets under the (Price-taker) Perfect Foresight strategy in Fig. 3. This figure illustrates significant variations across different years, as well as differences between markets.

If a price-taker operator would have invested in a battery of 4 MWh, acting only in the day-ahead market, and using the Perfect Foresight strategy to determine its charging and discharging, the annual operational profits that would have been obtained would reduce from year to year since 2006, reaching lows during 2016–2019, before increasing in 2021 and peaking in 2022. This observed pattern correlates with observed volatility in electricity prices in Fig. 2, showing that the benefits of battery-storage operators are strongly related to the presence and magnitude of price fluctuations. The differences in operational profits between years are substantial. For example, (nominal) annual operational profits in the day-ahead market in 2022 (191 thousand Euro) are over 9 times as large as in 2019 (21 thousand Euro). Historically, only in 2006, 2022 and 2023 did the prices in the day-ahead market show sufficient volatility to find a positive NPV. In the other years, the volatility of day-ahead prices was less, making that the installation costs should reduce before investing in a battery would become economically viable. In Appendix E, where we show the required cost reduction rates per year, it can be seen that these required cost reduction rates can be up to 75%. The profitability of a battery depends thus largely on the market conditions of the electricity market it operates in.

If the price-taker operator would have acted in the intraday market instead of the day-ahead market, the profitability would have increased due to the greater volatility of electricity prices in that market. Due to this greater volatility, the intraday market offers more opportunities for temporal arbitrage, resulting in both higher operational profits and higher NPV. The NPV is positive for all three considered years, indicating that, if electricity prices remain as volatile as in the recent three years, investments in batteries are economically viable.

Interestingly, the possibility to act first in the day-ahead market, and then in the intraday market, potentially leading to between-markets energy arbitrage opportunities, where electricity is bought in one market and simultaneously sold in the other market, does not lead to

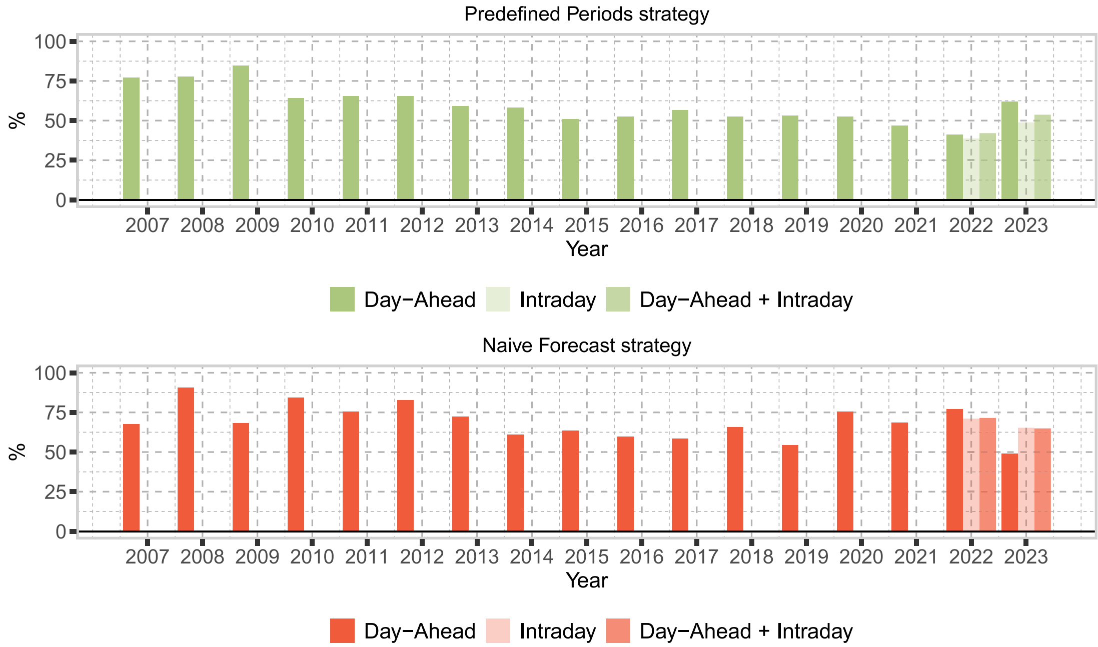

Fig. 4. Relative annual operational profits of price-taker battery-storage operator operating in the Dutch day-ahead (2007–2023) and/or intraday markets (2022–2023) with a storage capacity of 4 MWh, charging capacity of 1 MW, discharging capacity of 1 MW, Predefined Periods and Naive Forecast strategy, per market.
Notes: Profits as a percentage of operational profits under the Perfect Foresight strategy.

higher operational profits. This is because participating in the day-ahead market restricts the storage operator's flexibility in the more volatile intraday market; arbitrage opportunities in the intraday market might be missed if the capacity of the battery is already committed to the day-ahead market. In the years considered, the benefits of between-markets arbitrage do not outweigh these limitations, such that operating in both markets does not increase the profitability that can be obtained by operating only in the intraday electricity market. This is also reflected in the hurdles shown in Appendix B, which are used to prevent excessive battery use. When operating in both markets, the hurdles (which maximize the NPV) for the day-ahead electricity market are significantly higher compared to when the storage operator is active only in the day-ahead market, reflecting the higher opportunity costs of operating in the day-ahead market. These higher hurdles limit the operations in the day-ahead market, and most profits are realized through intraday market operations.

Summarizing, using temporal energy arbitrage can be profitable for batteries under the assumptions of perfect foresight and exogenous prices, if electricity prices are as volatile as in most recent years in the day-ahead and intraday auction markets. Highest profits can be realized in the intraday auction market, where electricity prices are more volatile. The addition of the option of between-markets energy arbitrage does not necessarily lead to increased operational profits. Only in 2006, 2022 and 2023 did the prices in the day-ahead market show sufficient volatility to find a positive NPV. For all other years, a significant cost reduction is needed to make investments in batteries profitable.

4.1.2. Predefined Periods and Naive Forecast strategy

To show the performance of the simple control strategies, Fig. 4 presents the annual operational profits of the Predefined Periods strategy and Naive Forecast strategy relative to the Perfect Foresight strategy in the same year. As the strategies use data from the previous year, only the relative profits of 2007–2023 (day-ahead) and 2022–2023 (intraday, day-ahead + intraday) are shown.

The simple strategies operate without knowledge of future prices, relying instead on patterns observed in historical electricity prices. As shown by the figure, these patterns allow storage operators to capture a substantial portion of operational profits. Across all time periods and markets, the Predefined Periods strategy secures 58% of the profits achieved with the Perfect Foresight strategy, while the Naive Forecast strategy captures even 66%. However, the performance of both strategies fluctuates over time and between different markets, which indicates that the market situations are sometimes more constant than in other cases.

For the Predefined Periods strategy, the difference in operational profits compared to the Perfect Foresight strategy can be explained by the design of the strategy. By purchasing during historically low-price periods and selling during historically high-price periods, the Predefined Periods strategy captures general patterns in electricity prices. However, this approach lacks the flexibility to adjust buying and selling, leading to lower profits than can be obtained under the Perfect Foresight strategy. The lower operational profits also result in a lower NPV, which are only positive in 2022 for the intraday market, and in 2022 and 2023 when the storage operator operates sequentially on the day-ahead and intraday electricity market. If the electricity prices are as volatile as in the other years, the installation costs of batteries should reduce to make investing in batteries economically viable. Some of these required cost reductions, which can be found in Table E.1 exceed 85%. This indicates that, in some years, the combination of the low variability of day-ahead prices and the limited flexibility of the Predefined Periods strategy results in operational profits that are much lower than required.

Compared to the Predefined Periods strategy, the Naive Forecast strategy is more dynamic, as it bases decisions on recent past optimal actions. Nevertheless, decisions that were optimal last week may prove suboptimal in the next, preventing the strategy from fully benefiting from fluctuations within and between markets. Moreover, the reliance on historical data to set the hurdle affects the profitability. Under the Perfect Foresight strategy, we balance the operational profits against the opportunity costs of using the battery by the storage operator, resulting in the highest NPV. However, this requires knowledge of future prices, which is not available under the Predefined Periods strategy. Therefore, the hurdle that was optimal in the preceding year is used, which affects the activity of the storage operator and thus the profitability. For example, in 2022, when electricity prices and

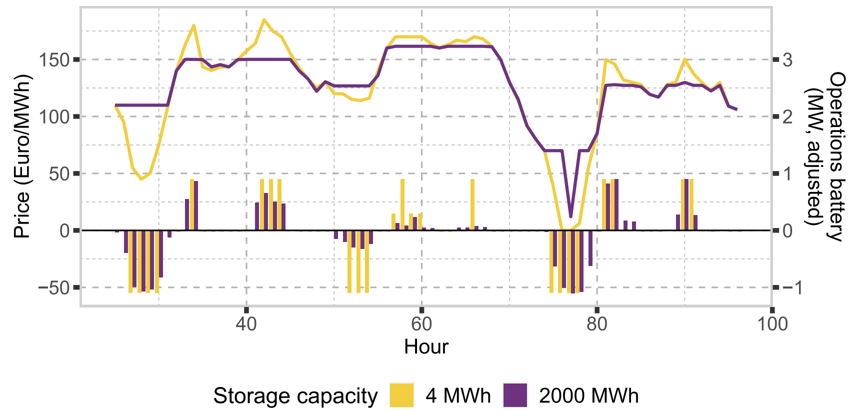

Fig. 5. Day-ahead electricity prices (left y-axis) and operations of 4-hour battery-storage operator (right y-axis) under the Perfect Foresight strategy, from January 2, 2023 to January 4, 2023 for different storage sizes.
Notes: The operations of the storage operator are adjusted, such that the maximum charging and discharging capacity is 1 MW.

fluctuations were high, the hurdle for maximizing NPV was high, as shown in Table B.1 in Appendix B. However, when the Naive Forecast strategy applies this hurdle from 2022 in 2023, a year with lower price volatility, fewer transactions were made, resulting in lower profits. If we use the same hurdles as for the Perfect Foresight strategy, the average performance of the Naive Forecast strategy over all years and markets increases to 70.8%. On average, the operational profits obtained under the Naive Forecast strategy are higher than under the Predefined Periods strategy. This also results in higher NPVs, which are positive in 2022 for the intraday market and the combined day-ahead and intraday market operations, and in 2023 for all three market position variations.

When examining the relative performance of the two simple strategies depicted in Fig. 4 over time, it seems that the relative performance of these strategies decreases in the day-ahead market over time, and that having knowledge of future prices has become more important over time. In the early years, when Dutch electricity generation was primarily based on fossil fuels, electricity prices followed relatively stable demand-driven patterns, enabling simple strategies to capture substantial profits. However, as renewable energy sources such as solar and wind, characterized by low marginal costs and fluctuating output, began to play a greater role, these predictable patterns were disrupted, leading to decreased profitability. Nonetheless, as renewables became even more prevalent, new price trends emerged, allowing for a renewed improvement in the performance of the simple strategies.

Hence, using batteries for energy arbitrage can also be profitable without perfect foresight of future electricity prices. By exploiting patterns in historical electricity prices, battery operators can still generate adequate profits under the assumption of exogenous prices, as long as price fluctuations are large enough, and patterns in electricity prices remain.

4.2. *Profitability of price-maker battery*

Up to this point, we have ignored the impact of the battery operator on electricity prices. This assumption simplifies the analysis but may not be valid anymore when the installed capacity of batteries increases. To test the importance of the price-maker formulation when more batteries are installed, we analyse day-ahead electricity prices and battery operator decisions from January 2 to January 4, 2023, under the Perfect Foresight strategy for different installed battery capacities in Fig. 5.

From Fig. 5 it is clear that the battery is charged during hours with low electricity prices, and discharged during hours with high prices. When the installed capacity of the storage operator is small (i.e. 4 MWh), the storage operator can offer full available capacity during the lowest and highest price periods (which are known in advance), as these bids do not notably affect electricity prices. However, when a large installed capacity (2000 MWh) of batteries would submit these full-capacity bids, the low prices during charging rise, and the high prices during discharging fall. Therefore, rather than offering full capacity to the market, battery-storage operators with perfect foresight of future prices and other bids, submit bids where the offered volume depends on the actual market clearing. As such, the charging and discharging are more spread over time. Over the entire year 2023, the battery-storage operator is active in 4736 h when 2000 MWh of storage capacity is installed, compared to 2699 h when only 4 MWh of storage capacity is installed. However, the average percentages of the available charging and discharging capacity that is used reduce from (almost) 100% to 53% (charge) and 63% (discharge) when 2000 MWh of battery capacity is installed. Hence, in a system with a large installed battery capacity, optimal charging and discharging operations depend not only on the volatility in prices, but also on the effect on prices.

4.2.1. *Perfect Foresight strategy*

The smoothened prices of the previous results indicate that energy arbitrage opportunities decrease when more batteries are installed, making investments in batteries less profitable. Fig. 6 shows the effects of increased battery installed capacity on annual operational profits and the corresponding NPV of batteries in different markets under the Perfect Foresight strategy in 2023.

When more batteries are installed and used for energy arbitrage in the day-ahead and/or intraday auction markets, operational profits and the corresponding NPV decline due to smaller price fluctuations. Because the intraday market is smaller than the day-ahead market in terms of traded volumes, the impact of battery operations is greater on the intraday market, causing both operational profits and NPV to decrease more rapidly in the intraday market than in the day-ahead market. Fig. 6 also highlights that between-markets arbitrage opportunities become increasingly important as battery installations grow. With little batteries installed, the more volatile intraday electricity prices are most attractive for battery-storage operators, i.e., the opportunity costs of operating first in the day-ahead market are relatively high. However, with diminishing arbitrage opportunities in the intraday auction market, these opportunity costs decrease, as the missed revenues caused by battery capacity not being available in the intraday market decrease. Therefore, the potential to generate revenues through between-markets arbitrage between the day-ahead and intraday markets becomes larger.

Similar conclusions can be drawn from Table 2, where we show the cost reduction γ that is required to make the NPV of investing in a battery non-negative. As more batteries are being installed, battery costs

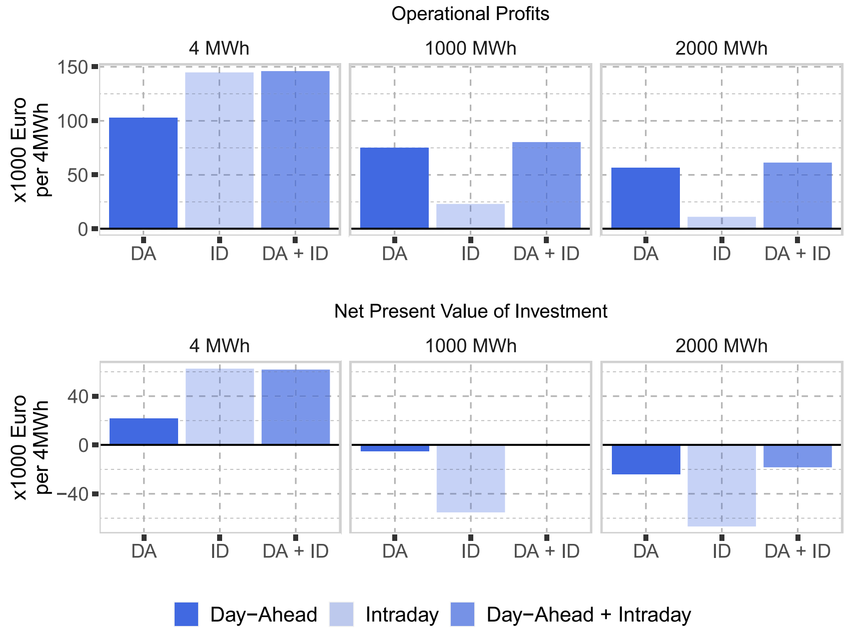

Fig. 6. Annual operational profits and Net Present Value (1000 euros) of 4-hour battery for different capacities, Perfect Foresight strategy, 2023, per market.
Notes: Charging and discharging capacity are 4 times as small as the storage size. Operational profits and NPV are scaled to the profits and NPV of a battery with a storage capacity of 4 MWh, charging and discharging capacity of 1 MW.

Table 2
Cost reduction γ (%) required to make NPV nonnegative of 4-hour battery for different capacities, Perfect Foresight strategy, 2023, per market.

Storage capacity	Market		
	Day-Ahead	Intraday	Day-Ahead + Intraday
4 MWh	0.0	0.0	0.0
1000 MWh	6.6	71.2	0.0
2000 MWh	30.4	86.1	23.6

Notes: Charging and discharging capacity are 4 times as small as the storage size.

should decrease to compensate for the decreasing arbitrage revenues. Battery costs should decrease most when the storage operator acts on the intraday market only, as operational profits decrease most in this market.

4.2.2. Other strategies

The previous analysis showed that the profitability of batteries decreases when more batteries are being installed under the Perfect Foresight assumption, where future prices and the own effect on prices are known. Next, we analyse the storage strategies that lack (all or part of) this information. To do so, we present the break-even level of storage capacity assuming no entry barriers and competitive behaviour in Table 3, that is, we show the installed capacities that result in an NPV equal to zero. We do this for different levels of cost reduction, to show how many batteries can be added to the electricity system when the costs of batteries decrease.

As operational profits decrease with increased battery deployment, battery costs must decrease to enable profitable expansion of battery storage capacity. This relationship is reflected in Table 3, where higher values of the cost reduction parameter γ correspond to greater break-even storage capacities across all storage strategies.

When the storage operator uses only temporal arbitrage within the day-ahead or intraday market (*Market = Day-ahead, Intraday* in Table 3), the optimal storage capacity is highest under the Price-taker Perfect Foresight strategy. With this strategy, the storage operator knows what future prices will be (without taking into account the own effect on prices), allowing it to maximize temporal arbitrage revenues. Among the two other strategies, the Naive Forecast strategy generally leads to the highest break-even storage capacity. This is in line with the price-taker analysis, which shows that the Naive Forecast generally outperforms the Predefined Periods strategy.

Similar to the results for the Perfect Foresight strategy, the effects of battery operations on prices are largest in the intraday market, which is less liquid than the day-ahead market. As a consequence, with a cost reduction rate $\gamma = 60\%$, the break-even levels of storage capacity in the day-ahead market are larger than the break-even capacities in the intraday auction market. However, for lower cost reduction rates ($\gamma = 0\%, \gamma = 30\%$), the break-even storage capacities are larger in the intraday market than in the day-ahead market for the Predefined Periods strategy and the Naive Forecast strategy. This can be attributed to the fact that with low cost reduction rates, limited battery capacity can be added to the system. For such small battery capacities, the effects on prices remain limited, such that temporal arbitrage opportunities in the intraday market are more profitable than in the day-ahead market.

Under the Predefined Periods strategy, between-markets arbitrage (*Market = Day-Ahead + Intraday* in Table 3) results in the storage operator operating in both the day-ahead and the intraday market. As such, the break-even battery capacity is larger than the capacity using only temporal arbitrage for small cost reductions ($\gamma = 0\%, \gamma = 30\%$), as the effects on (intraday) prices are limited. When battery costs are lower ($\gamma = 60\%$), more batteries can be added to the system, resulting in larger price effects, For this cost reduction rate, the break-even storage capacity of the between-market arbitrage is higher than that of the Predefined Periods strategy in the intraday market, but smaller than in the day-ahead market.

The other two strategies are based on expected price levels, without taking into account the effect on prices. Under the price-taker assumption, most profits can be made in the intraday market. As a consequence, under the Naive Forecast strategy and Price-taker Perfect Foresight strategy, where the effect on prices is not taken into account, most electricity is traded on the intraday market. Hence, the break-even levels of storage capacity are only slightly higher than in the situation where the storage operator acts in the intraday market only.

These findings suggests that operating batteries profitably becomes increasingly challenging when more batteries are being installed, and highlights the growing importance of having knowledge of future market conditions and applying more advanced storage-operations strategies.

Table 3
Break-even level of storage capacity (MWh) assuming no entry barriers and competitive behaviour, per strategy and market, for different reductions in battery costs.

Strategy	Cost reduction γ (%)	Market		
		Day-ahead	Intraday	Day-ahead + Intraday
Predefined Periods	0%	0.0	0.0	0.8
	30%	1.6	54.4	179.6
	60%	899.2	136.8	294.8
Naive Forecast	0%	0.0	73.6	74.8
	30%	0.0	143.6	144.8
	60%	1080.0	196.0	197.2
Price-taker Perfect Foresight	0%	670.0	187.2	188.8
	30%	1566.4	238.8	240.4
	60%	2515.2	278.4	279.2

Notes: Charging and discharging capacity are 4 times as small as the storage size. Under the Price-taker Perfect Foresight strategy, the storage operator perfectly predicts future prices, but effects on the prices are ignored.

5. Conclusion

In future electricity systems, energy storage systems such as batteries are expected to play an important role due to their ability to transport energy in time. In this study, we have investigated the profitability of investments in batteries that use energy arbitrage in and between the day-ahead and intraday auction electricity markets. Our main contribution is that, in addition to the conventional price-taker approach, we explicitly look at alternative operation strategies and market dynamics with endogenous electricity prices, where the effects of the decisions of battery-storage operators are taken into account.

A battery-storage operator that uses energy arbitrage generates profits from fluctuating electricity prices by charging when electricity prices are low, and discharging when prices are high. As the day-ahead and intraday markets are parallel markets, arbitrage opportunities arise from both intra-market price variations over time and between-market price differences. However, benefiting from these price fluctuations is non-trivial, as decisions on when to charge and discharge the battery have to be made before the prices are known. Moreover, in an electricity system with many battery operators trying to benefit from price fluctuations, the effect of storage operations on prices should be taken into account, which also makes the operation of batteries more complex.

Using an electricity market model along with historical data on electricity prices, quantities, and exchange bidding data, we have analysed the profitability of investments in batteries in the Netherlands. We have done this first under the conventional price-taker assumption, where prices are considered fixed, and explored the impact on profitability when this assumption is relaxed, accounting for the actions of battery-storage operators. Moreover, we have considered different operation strategies, determining the timing and volume of charging and discharging. These strategies differ in their approach to estimate future price volatility, and provide upper- and lower bounds of the batteries' profitability.

Under the assumption of exogenous prices, which is equal to saying that the size of installed batteries is negligible, we find that temporal arbitrage can be profitable for batteries if prices are as volatile as in recent years. Moreover, in the case of a low amount of installed battery capacity, we find that perfect foresight of future prices is not essential for successful battery operation in energy arbitrage, as strategies based on historical price patterns can capture a substantial portion of the profits achieved under perfect foresight. Previous studies on the profitability of battery energy storage in day-ahead electricity markets (Arcos-Vargas et al., 2020; Hu et al., 2022; Komorowska and Olczak, 2024) concluded that energy arbitrage is not economically viable in most European day-ahead electricity markets. However, these analyses were based on older data, reflecting periods of lower price volatility and higher battery costs, which may explain the differing conclusions.

Due to the higher volatility of intraday-electricity prices, most profits can be made in this market, and the added complexity of between-markets energy arbitrage between the day-ahead and intraday auction markets does not significantly increase profitability. These findings are consistent with the results of Metz and Saraiva (2018), who conducted a similar study on the German electricity market for the period 2011–2016.

However, when more batteries are installed and their impact on electricity prices is considered, these findings change. First, the smoothing effect of battery operations on prices leads to a decline in battery profitability when more batteries are added to the system. Additionally, as battery capacity increases, the value of between-markets energy arbitrage becomes more significant, since profits in the intraday market decline faster than those in the day-ahead market. Furthermore, operating a battery without perfect foresight of future prices and the impact of batteries on the prices becomes more challenging, as existing price patterns can be disrupted once batteries start exploiting them. Therefore, accurately predicting future market conditions becomes increasingly valuable for optimizing battery operations.

Under the assumption of operating batteries with perfect knowledge of what future prices would be without the impact of battery operations, and a cost reduction of battery installation costs of 60%, our analysis shows that around 2515 MWh of 4-hour batteries could have been added to the Dutch electricity system in 2023 while remaining profitable. Considering a home battery for households with a capacity of 6 kWh (Milieu Centraal, 2025), this boils down to almost 420,000 home batteries, such that 14% of the three million Dutch households with solar panels can own a battery. Given that also other, large-scale batteries are expected to be added to the Dutch electricity system, there seems to be relatively little space for additional (household) batteries, or, the other way around, for many more large-scale battery projects.

The numerical results are, of course, sensitive to the assumptions made. The results in this study are, for example, based on data from the Dutch electricity system from 2006–2023 and technological assumptions on battery-storage systems. Given the potential geographical variation in battery-storage profitability (Komorowska et al., 2022; Mercier et al., 2023), the evolving costs and performance of batteries (Cole et al., 2021), and the introduction of additional intraday electricity markets (ENTSOE, 2024), our results may not directly apply to other countries or different battery technologies. However, as most European electricity markets have a similar design to the Dutch electricity market, and the introduction of additional intraday markets does not alter this fundamental structure, we believe that our key insights regarding battery profitability remain broadly applicable. The analysis of price-maker batteries relies on data from 2023. In terms of electricity prices, this year was not unique: day-ahead prices in 2024 have shown a similar level of volatility, suggesting that our results are generalizable. However, electricity markets are constantly evolving, and this movement will continue. For example, in 2024, additional intraday markets were introduced (ENTSOE, 2024), offering new arbitrage opportunities for battery storage operators. At the same time, the share of renewables in the system has increased, and is expected to further increase, making the role of energy storage systems such as batteries more prominent. It is therefore important to keep investigating the profitability of batteries. As the proposed methodology can be adapted to any pay-as-cleared electricity market with an auction-clearing mechanism and any set of battery technological parameters, the methodology is suitable for future research exploring battery profitability in other countries, additional intraday auctions closer to delivery, or alternative storage technologies.

Another research direction could be further exploration of between-markets arbitrage opportunities between the day-ahead and intraday electricity markets. In this study, we only considered the case where a storage operator sequentially trades in these two markets. An alternative approach would involve investigating both markets simultaneously, allowing decisions in the day-ahead market to account for trading in the intraday market. Examples of this type of analysis can be found in Metz and Saraiva (2018) and Finnah et al. (2022). However, these studies only consider exogenous prices, which requires additional constraints to reduce speculation on the price difference between the two markets. Our methodology, where we use an electricity-market model, would circumvent these additional constraints, as the effect on prices is taken into account.

In addition, further research could involve exploring alternative revenue streams for batteries, and compare battery storage systems with alternative options that provide flexibility. Our current focus on day-ahead and intraday market arbitrage assumes that batteries operate exclusively within these markets, but they may also generate income from other sources. Considering additional revenue streams, such as ancillary services (Maeyaert et al., 2020) or capacity markets (Strbac et al., 2017; Gailani et al., 2020), would offer a more comprehensive assessment of the economic viability of battery-storage systems. By comparing batteries with alternative sources of flexibility, see e.g. Golombek et al. (2022), one could further evaluate the economic value of batteries with grid-scale storage. The Dutch electricity grid is, for instance, connected to the Norwegian grid, where hydro storage plays a prominent role. Comparing the investment in batteries with further expanding the transmission capacity between the two markets would contribute to a better understanding of the economic value of batteries compared to alternative flexibility sources.

By using bidding data, our analysis takes into account that only a part of all electricity is traded on day-ahead and intraday auction markets, and we eliminate the need to make assumptions on the bidding behaviour of different market participants. However, by assuming that the bidding curves remain unchanged when more batteries are being installed, we ignore that bidding behaviour might change when more batteries are being installed, and we also ignore international effects due to market coupling. On the one hand, the presence of batteries might affect the supply by other flexible sources. If the supply of flexibility by these sources decreases due to decreasing price fluctuations caused by increased battery capacity, our analysis might slightly underestimate the value of batteries. However, if batteries are used in combination with other assets, price fluctuations might decrease, such that our analysis overestimates the profitability of batteries. The latter may also be the case when battery operators have to pay for making use of the grid, while in the current analysis it is implicitly assumed that all batteries are installed behind the meter without additional grid costs.

In addition, we have focused on the electricity-market structure between 2006–2023. As the intraday auction market was only recently introduced in the Netherlands, this market may still develop (Braun, 2016). As this market matures, the numerical results may vary, potentially leading to a slower decrease in operational profits with increased battery installations. Despite these considerations, we do not expect the general insights from our analysis to change significantly. Thus, the profitability of battery investments is influenced by the magnitude of the total installed capacity of batteries, which is a relevant consideration for potential investors.

CRediT authorship contribution statement

Arjen T. Veenstra: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Machiel Mulder:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Appendix A. Nomenclature

See Tables A.1 and A.2.

Appendix B. Strategy-specific parameters

B.1. Price-taker battery operator

Table B.1 shows the strategy-specific parameters per market and year, under the price-taker assumption.

The charging and discharging decisions made by storage operators are influenced by price-specific parameters. These parameters are determined through the calculation of the NPV, which takes into account various factors, including the calendric lifetime limit and the operational limit (see Eq. (18)). While the calendric lifetime is fixed and exogenous, the operational limit is determined by the storage operator's activities and, therefore, by the strategy-specific parameters. Similar to Metz and Saraiva (2018), we find that the strategy specific parameters that maximize the NPV are such that the number of cycles lies around 333. At this level of activity, both the calendric lifetime limit (15 years) and the operational limit (5,000 cycles) are reached simultaneously.

B.2. Price-maker battery

Table B.2 shows the hurdles for the Perfect Foresight strategy per market in 2023 for different battery capacities, under the price-maker assumption. The parameters of the Predefined Periods, Naive Forecast and Price-taker Perfect Foresight strategies are the same as under the price-taker assumption in 2023, and can be found in Table B.1.

Under the price-taker assumption, the optimal hurdles for maximizing the NPV are those where the battery uses about 330 cycles per year, and the lifetime limit and operational limit are aligned. However, when more batteries are being installed en the effects on electricity prices are considered, this alignment holds only in the day-ahead market. In the intraday market, the price effects are more pronounced, meaning that the target of 330 cycles per year is not achievable to make a positive operational profit when additional battery capacity is installed (e.g., 1000 MWh, 2000 MWh). In these situations, the hurdle rate must balance between achieving more cycles (which requires a lower hurdle) and capitalizing on larger price differences (which demands a higher hurdle).

Table A.1
Overview of notation used in analysis of price-taker battery operator.

Sets and indices	
$\mathcal{T}$	Periods, $\mathcal{T} = \{1, 2, \dots, T\}$
t	Period, $t \in \mathcal{T}$
m	Day-ahead electricity market (DA), Intraday auction market (ID)
Decision variables storage operator	
$q_m^b(t)$	Amount of electricity bought
$q_m^s(t)$	Amount of electricity sold
$q^{in}(t), q^{out}(t)$	Amount of electricity charged, discharged
$S(t)$	Storage level at the start of period
System parameters	
S^M	Storage capacity
S^0	Initial storage level
C^C	Charging capacity
C^D	Discharging capacity
η^C	Charging conversion efficiency
η^D	Discharging conversion efficiency
$H^{\mathrm{DA}}, H^{\mathrm{ID}}$	Hurdle rate used on day-ahead market, intraday market
K^S	Costs battery, per MWh storage capacity
K^C	Costs battery, per MW charging capacity and discharging capacity
L^{CAL}	Calendric lifetime
L^{CYC}	Cycle lifetime
r	Discount factor
Exogenous information	
$p_m(t)$	Electricity price
Parameters, Perfect Foresight strategy	
T^{PF}	Number of future periods of which the storage operator has perfect knowledge
Parameters, Predefined Periods strategy	
$\mathcal{T}_m^B$	Set of periods in which electricity is bought
$\mathcal{T}_m^S$	Set of periods in which electricity is sold
$\mathcal{T}_m^{B,\mathrm{day}}$	Set of periods within a day in which electricity is bought
$\mathcal{T}_m^{S,\mathrm{day}}$	Set of periods within a day in which electricity is sold
$S^{\mathrm{noDA}}, S^{\mathrm{DA}}, S^{\mathrm{ID}}$	Quarterly storage levels without day-ahead operations, with day-ahead operations, and with both day-ahead and intraday operations
Δb	Change in storage level
Parameters, Naive Forecast strategy	
$T^{\mathrm{NF,f}}$	Number of future periods for which the storage operator plans its actions
$T^{\mathrm{NF,b}}$	Number of periods the storage operator looks back
Performance metrics	
Π	Operational profits
NC	Number of cycles
NPV	Net Present Value of investment

Table A.2
Overview of additional notation used in analysis of price-maker battery operator.

Sets	
$\mathcal{B}_m(t)$	Buying bids, $\mathcal{B}_m(t) = \{1, \dots, B_m(t)\}$
$\mathcal{S}_m(t)$	Selling bids, $\mathcal{S}_m(t) = \{1, \dots, \mathcal{S}_m(t)\}$
Decision variables	
$q_m^{b,i}(t)$	Amount of electricity bought by market participant with bid $i \in \mathcal{B}_m(t)$
$q_m^{s,j}(t)$	Amount of electricity sold by market participant with bid $j \in \mathcal{S}_m(t)$
Bidding parameters	
$Q_m^{b,i}(t)$	Quantity bid by market participant with bid $i \in \mathcal{B}_m(t)$
$Q_m^{s,j}$	Quantity bid by market participant with bid $j \in \mathcal{S}_m(t)$
$\mathrm{WTP}_m^i(t)$	Price bid by market participant with bid $i \in \mathcal{B}_m(t)$ (willingness-to-pay)
$\mathrm{MC}_m^j(t)$	Price bid by market participant with bid $j \in \mathcal{S}_m(t)$ (marginal cost)
$\bar{p}^m$	Price bid by storage operator trying to sell electricity, under Predefined Periods- and Naive Forecast strategy, and price paid by storage operator if selling bid cannot be fulfilled
$\underline{p}^m$	Price bid by storage operator trying to buy electricity, under Predefined Periods- and Naive Forecast strategy, and price paid by storage operator if buying bid cannot be fulfilled

Table B.1
Hurdle rate (Euro/MWh) for Perfect Foresight (PF) and Naive Forecast (NF) strategy, and periods of buying and selling for Predefined Periods (PP) strategy, used in the analysis of price-taker battery-storage operator, per year in day-ahead (DA), intraday (ID), and day-ahead and intraday (DA + ID)

Market	Year	Strategy			
		PF	NF	PP	
		Hurdle	Hurdle	$\mathcal{T}_{DA}^{B,d}$ (hours), $\mathcal{T}_{ID}^{B,d}$ (quarters)	$\mathcal{T}_{DA}^{S,d}$ (hours), $\mathcal{T}_{ID}^{S,d}$ (quarters)
DA	2006	13.50	–	–	–
	2007	7.10	13.50	{3, 4, 5, 6}	{10, 11, 18, 19}
	2008	10.80	7.10	{2, 3, 4, 5, 6, 7, 8}	{11, 12, 18, 19, 20, 21, 22}
	2009	6.40	10.80	{2, 3, 4, 5, 6, 7}	{10, 11, 12, 19, 20, 22}
	2010	5.50	6.40	{3, 4, 5}	{11, 19, 20}
	2011	4.35	5.50	{3, 4, 5}	{11, 19, 20}
	2012	6.10	4.35	{3, 4, 5}	{11, 19, 20}
	2013	5.80	6.10	{3, 4, 5}	{11, 19, 20}
	2014	4.05	5.80	{3, 4, 5}	{11, 19, 20}
	2015	4.85	4.05	{3, 4, 5}	{11, 18, 19}
	2016	3.40	4.85	{3, 4, 5}	{9, 11, 19}
	2017	3.45	3.40	{3, 4, 5}	{18, 19, 20}
	2018	4.85	3.45	{3, 4, 5}	{9, 18, 19}
	2019	3.35	4.85	{3, 4, 5}	{9, 19, 20}
	2020	4.70	3.35	{3, 4, 5}	{8, 19, 20}
	2021	8.50	4.70	{3, 4, 5}	{8, 19, 20}
	2022	27.05	8.50	{3, 4, 14}	{8, 19, 20}
	2023	14.05	27.05	{4, 13, 14, 15}	{8, 18, 19, 20}
ID	2021	17.60	–	–	–
	2022	29.80	17.60	{4, 8, 12, 16, 17, 40, 52, 53, 57, 61, 65, 92, 96}	{29, 32, 33, 37, 68, 71, 72, 73, 76, 77, 81, 85, 89}
	2023	28.10	29.80	{4, 8, 12, 25, 29, 40, 44, 47, 48, 52, 53, 57, 61, 65, 92, 96}	{29, 32, 33, 37, 41, 68, 71, 72, 73, 76, 77, 78, 80, 81, 89, 93}
DA + ID, DA	2021	42.30	–	–	–
	2022	89.80	42.30	{3}	{19}
	2023	186.00	89.80	{13, 14}	{19, 20}
DA + ID, ID	2021	17.95	–	–	
	2022	29.95	17.95	{4, 8, 12, 16, 17, 40, 52, 53, 57, 61, 65, 92, 96}	{29, 32, 33, 37, 68, 71, 72, 73, 76, 77, 81, 85, 89}
	2023	28.00	29.95	{12, 48, 52, 53, 57, 61, 65, 96}	{29, 33, 37, 68, 71, 72, 73, 76}

Notes: Perfect Foresight strategy: hurdle rate that maximizes NPV. Naive Forecast strategy: hurdle rate that maximizes NPV of previous year. Predefined Periods strategy: $\mathcal{T}^B$ is the set of periods in which electricity is bought, $\mathcal{T}^S$: is the set of periods in which electricity is sold. Under the price-taker assumption, the hurdles of the Price-taker Perfect Foresight strategy are the same as for the Perfect Foresight strategy.

Table B.2
Hurdle rate (Euro/MWh) for Perfect Foresight strategy used in the analysis of price-maker battery-storage operator, 2023, in day-ahead (DA), intraday (ID), and day-ahead and intraday (DA + ID), for different storage capacities.

Market	Storage capacity		
	4 MWh	1000 MWh	2000 MWh
DA	14.05	9.60	5.70
ID	28.10	27.90	28.20
DA + ID, DA	186.00	14.40	6.90
DA + ID, ID	28.00	25.90	24.70

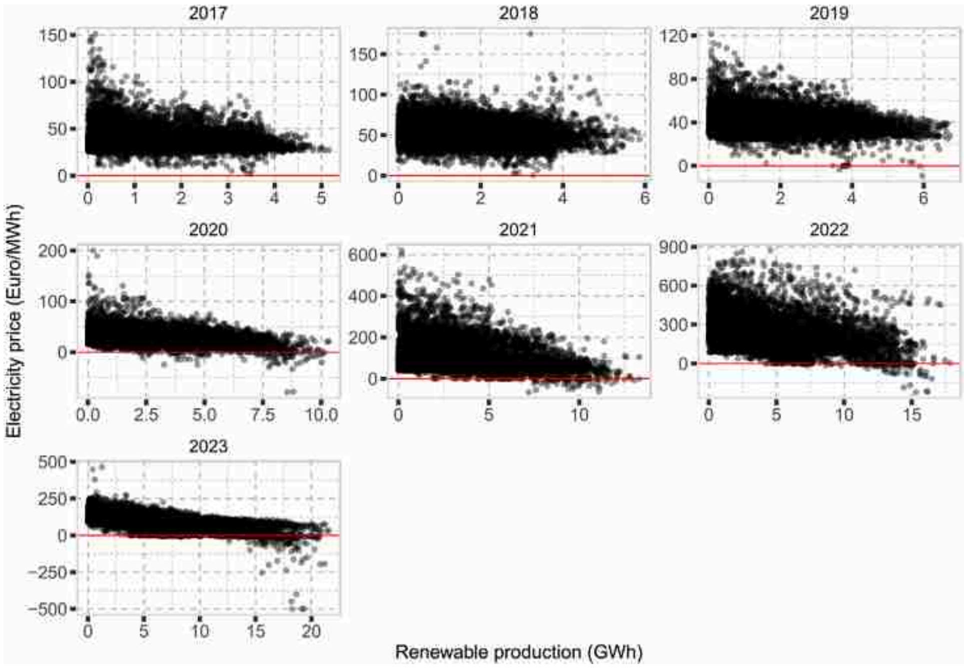

Fig. D.1. Scatterplots of Dutch renewable electricity production (GWh) and day-ahead electricity prices (Euro/MWh) for the period 2017–2023, per year.
Notes: Data on hourly renewable production comes from National Energie Dashboard (NED, 2025). For each hour, we sum the production of solar PV (zonne-energie), onshore wind (Windenergie op land) and offshore wind (Windenergie op zee).

Appendix C. Predefined Periods strategy, intraday operations

In the intraday, the storage operator decides at period $t \in \{1, 5, \dots, T-3\}$ the amounts of electricity bought or sold in the intraday market. In predefined quarters, the storage operator buys or sells as much electricity as possible, given charging constraints, available storage capacity, and the actions in the day-ahead electricity market. To account for these operations in the day-ahead market, we define additional storage variables S^{noDA}, S^{DA}, and S^{ID}. S^{noDA} is a vector of length four, indicating the storage level per 15 min, without taking into account the operations on the day-ahead market:

$$S^{\text{noDA}} = (s^{\text{noDA}}(1), s^{\text{noDA}}(2), s^{\text{noDA}}(3), s^{\text{noDA}}(4)) = (S(j), S(j), S(j), S(j)). \tag{C.21}$$

S^{DA} is also a vector of length four, indicating the quarterly storage level with the operations on the day-ahead market included:

$$S^{\text{DA}} = (s^{\text{DA}}(1), s^{\text{DA}}(2), s^{\text{DA}}(3), s^{\text{DA}}(4)), \tag{C.22}$$

where

$$s^{\text{DA}}(1) = S(t) + q^b_{\text{DA}}(t)\eta^C - q^s_{\text{DA}}(t)/\eta^D, \tag{C.23a}$$

$$s^{\text{DA}}(l) = s^{\text{DA}}(l-1) + q^b_{\text{DA}}(t+l-1)\eta^C - q^s_{\text{DA}}(t+l-1)/\eta^D, \quad l = 2,3,4. \tag{C.23b}$$

Finally, S^{ID} indicates the storage level after the day-ahead and intraday operations are determined.

The operations on the intraday market are determined per quarter, for every $l = 0,1,2,3$:

$$q^b_{\text{ID}}(t+l) = \begin{cases} \min\left\{C^C - q^b_{\text{DA}}(t+l), \frac{S^M - s^{\text{DA}}(4)}{\eta^C}, \frac{S^M - s^{\text{noDA}}(l+1)}{\eta^C}\right\} + q^s_{\text{DA}}(t+l) & \text{if } t+l \in \mathcal{T}^B_{\text{ID}}, \\ 0 & \text{otherwise}, \end{cases} \tag{C.24a}$$

$$q^s_{\text{ID}}(t+l) = \begin{cases} \min\{C^D - q^s_{\text{DA}}(t+l), s^{\text{DA}}(4)\eta^D, s^{\text{noDA}}(l+1)\eta^D\} + q^b_{\text{DA}}(t+l) & \text{if } t+l \in \mathcal{T}^S_{\text{ID}}, \\ 0 & \text{otherwise}, \end{cases} \tag{C.24b}$$

After each quarter, the storage variables are updated. We therefore define the total change in battery level Δb:

$$\Delta b = q^b_{\text{DA}}(t+l) + q^b_{\text{ID}}(t+l) - q^s_{\text{DA}}(t+l) - q^s_{\text{ID}}(t+l) \tag{C.25}$$

which is used as follows. If $\Delta b \le 0$:

$$S^{\text{ID}}(t+l) = s^{\text{noDA}}(t+l) + \Delta b/\eta^D, \tag{C.26}$$

$$s^{\text{noDA}}(t+l) = s^{\text{noDA}}(t+l) + \Delta b/\eta^D. \tag{C.27}$$

Alternatively, if $\Delta b > 0$:

$$S^{\text{ID}}(t+l) = s^{\text{noDA}}(t+l) + \Delta b\eta^C, \tag{C.28}$$

$$s^{\text{noDA}}(t+l) = s^{\text{noDA}}(t+l) + \Delta b\eta^C. \tag{C.29}$$

We also update S^{DA}:

$$S^{\text{DA}} = S^{\text{DA}} - (s^{\text{DA}}(l+1) - S^{\text{ID}}(t+l)). \tag{C.30}$$

Updating storage level. After the operations in all quarters are determined, the storage level that is used in the next hour $S(t+4)$, is updated, by setting it equal to $S^{\text{DA}}(4)$.

Appendix D. Renewable electricity production, gas prices, and electricity prices

Fig. D.1 shows the relationship between Dutch renewable generation (solar PV, onshore wind and offshore wind) and Dutch day-ahead electricity prices for the years 2017–2023.

Fig. D.2 shows the relationship between price of natural gas and Dutch day-ahead electricity prices for the years 2006–2023.

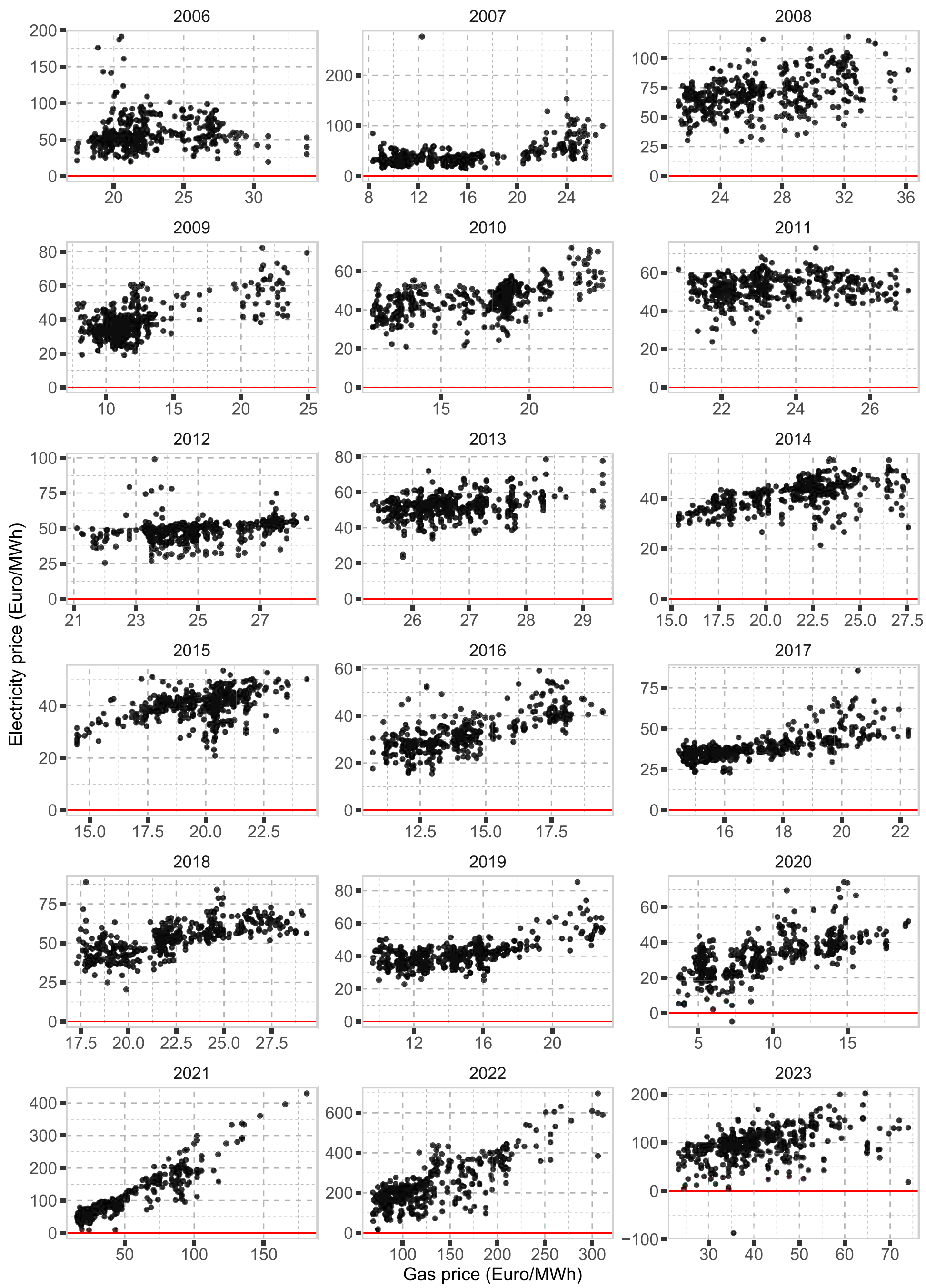

Fig. D.2. Scatterplots of gas price (Euro/MWh, daily) and day-ahead electricity prices (Euro/MWh, daily average) for the period 2006–2023.
Notes: Data on daily natural gas prices come from Bloomberg (2024), we take the natural gas day-ahead futures contract traded at the Title Transfer Facility (TTF) in the Netherlands.

Table E.1
Cost reduction γ (%) required to make NPV nonnegative, per year, in day-ahead market, intraday market, and both markets, price-taker storage operator.

Market	Year	Strategy		
		Perfect foresight	Naive forecast	Predefined periods
Day-Ahead	2006	0.0	–	–
	2007	19.5	45.6	43.5
	2008	11.6	24.8	37.4
	2009	51.9	67.0	62.8
	2010	60.6	66.6	74.7
	2011	64.7	73.2	77.0
	2012	56.4	65.8	71.5
	2013	57.8	69.3	75.0
	2014	68.0	80.3	81.4
	2015	66.4	79.5	83.0
	2016	72.9	83.6	85.8
	2017	70.0	82.3	83.1
	2018	63.2	78.9	80.7
	2019	74.1	85.7	86.3
	2020	65.1	76.7	81.7
	2021	7.2	51.1	56.5
	2022	0.0	0.0	3.0
	2023	0.0	37.2	27.6
Intraday	2021	0.0	–	–
	2022	0.0	0.0	9.4
	2023	0.0	0.0	0.0
Day-Ahead +Intraday	2021	0.0	–	–
	2022	0.0	0.0	0.0
	2023	0.0	0.0	0.0

Notes: For year y, the Net Present Value is calculated under the assumption that the electricity-price patterns of year y remain the same in each of the future years during the lifetime of the battery.

Appendix E. Required cost reduction, price-taker strategies

Table E.1 shows the required cost reduction in order to make NPV nonnegative per market and year, under the price-taker assumption.

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