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Avoiding avalanches: Effective dispatch planning for competing storage units in day-ahead electricity market simulations

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ABSTRACT

In electricity markets, storage operation and bidding strategies are based on expected price spreads. At the same time, these spreads are affected by the operation of the storages. If many storage units react to an expected price spread in a similar way, their joint operation can significantly reduce the spread realised on the market. Such repercussions are known as “avalanche effects”. This paper examines dispatch planning strategies in agent-based electricity market simulations that counter those avalanche effects. These strategies utilise a dynamic programming algorithm to determine asks and bids. The algorithm can pursue different optimisation targets combined with varying awareness levels for price impacts. We apply these strategy variants to a parametrisation of the German electricity market and compare resulting prices, dispatch, and monetary performance to their historical values. Our findings illustrate that, without price impact awareness, storage units are 220% overused in simulations leading to high monetary losses. System-cost minimisation yields the highest correlation (86%) with the historical dispatch, but electricity prices are reproduced most accurately (87% correlation) using profit maximisation. Disaggregating storage units results in a better fit to historical data than an aggregated single-unit representation. Discharged energies and operational profits vary strongly across the different modelling experiments. Our research highlights the importance of detailed storage modelling to accurately assess storage market values. One identified strategy is based on implicit collusion and requires only minimal data also available in the real world. If storage operators behave accordingly, market monitoring and antitrust regulations may be required.

1. Introduction

As intermittent renewable energy generation technologies, such as wind and solar power, replace fossil-fuel power plants around the world [1], balancing electricity supply and demand becomes more challenging [2]. Energy storage systems, such as battery storage or pumped hydro storage, can contribute to this balance at varying temporal scales. Applications range from short-term to seasonal storage and from small-scale to large scale systems [3]. Especially battery storage systems also gain an increasingly important role in wholesale electricity markets [4]. For instance, in Germany, the installed capacity of large-scale battery storage rose already to more than 2 GW [5]. In addition, there are around 220 GW of network connection requests for large-scale storage systems [6], of which 24 GW are assumed to be viable [7]. An ongoing decline of storage costs is fostering this development. Battery pack prices in China have declined from around 260 $/kWh to below 100 $/kWh between 2017 and 2024 [8].

In future systems, large energy storage capacities may have a significant impact on electricity price dynamics [9]. If such impacts are not properly accounted for during dispatch planning, the resulting dispatch is suboptimal. For example, if one storage operator expects very low electricity prices at time A and very high prices at time B, this could result in charging and discharging actions planned for time A and B, respectively. If many operators have a similar price expectation, their combined dispatch could raise prices at time A and lower prices at time B leading to significantly reduced – or even inverted – price spreads. Such outcomes are known as “avalanche effects” and have been observed in models regarding, e.g., household demand-side flexibility [10], the heating sector [11], and the transport sector [12,13]. This highlights the need for novel methods to assess the profitability and system effects of storage systems. These methods need to consider that the economic perspective of individual storage units is influenced by the market environment comprising numerous competitors. It is therefore of great importance to account for the influence of competitors and to model the behaviour of a storage unit accurately [14].

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Nomenclature

Dispatch Planning

t	time step indices
P	offer price of an electricity ask or bid
V	value of a discretised storage level
i	initial storage level at the beginning of a transition
f	final storage level at the beginning of a transition
ΔE	energy delta of a transition
p	(expected) electricity price
p'	expected electricity price including dispatch from own storage
p''	expected electricity price including dispatch from all storages

Forecasting

t, t'	time step indices
m	storage dispatch multiplier estimate
m_0	initial storage dispatch multiplier estimate
$\overline{m}$	average storage dispatch multiplier estimate
j, k	indices of storage units
N	total number of storage units
C^{c}	installed charging capacity
C^{d}	installed discharging capacity
A	awarded energy per time step
τ	decay time for multiplier estimates
ω_0	initial weight multiplier

1.1. Related work

Optimisation models are commonly used to model electricity systems, focusing on minimising system costs under assumptions of perfect competition and central planning [15,16]. However, they do not account for strategic behaviour of individual investors and operators seeking to maximise their profit. Game-theoretic approaches can address this shortcoming and also assess market power [17]. Yet, most models also assume perfect information.

Agent-based models (ABMs) offer a way to incorporate imperfect information and strategic behaviour, simulating real-world actors' decision-making processes in electricity markets [18]. These models have been used to explore electricity markets [19] and allow modellers to analyse economic perspectives for storage operators in current and future scenarios, considering repercussions from the overall system [20].

Research on bidding strategies for energy storage systems, such as hydroelectric plants, is well-established [21,22]. [23] develop a profit-maximising strategy for battery storage systems, but neglect competition and market price impacts. This limitation is also found in [24], who propose a profit-maximising dynamic programming scheduling strategy for pumped hydro storage. The investigation of competition between different flexibility options (FOs), e.g., energy storage and demand-side flexibility, is covered to a lesser extent. [25] deploy a two-stage stochastic optimisation model and find substitutional competition between the FOs, but do not provide diverse operational strategies. [26] apply a multi-stage optimisation approach for three competing storage units and find that storage profits are significantly higher when the units coordinate their dispatch. Without dispatch coordination, however, storage profits and dispatch patterns were unstable.

As computational power increases, deep-reinforcement learning (DRL) models are emerging for simulating electricity markets [27]. Yet, they often fail to consider price impacts or provide interpretable results [28]. [29] use DRL to find intelligent bidding strategies of prosumers to be submitted to local electricity markets. However, the behaviour of prosumers on local energy community markets differs from that of large scale units on day-ahead markets. Thus, the transfer of results to those markets requires more work. In the study by [30], a price-making storage is considered. They find that a new strategy based on an actor-critic approach outperforms a baseline strategy. However, the integration of competition among multiple FOs with market power remains unexplored. A robust strategy, even when competing FOs are taken into account, is presented in [31]. However, the case study is performed on historical market data only. Further work is needed to assess the performance of these models under high renewable energy shares.

1.2. Novelty

While there is a substantial amount of literature on bidding strategies for storage units, our work offers several key methodological advantages, while following a thorough open science approach. First, we develop a flexible scheduling algorithm using dynamic programming which allows to study price-taking as well as price-making strategies. Additionally, we include a sophisticated approach to account for price effects of multiple storage units. This enables us to study the implications of competing storage units and to explicitly control avalanche effects. While we provide no direct quantitative measure for avalanche effects, we provide benchmarks for the dispatch planning algorithm variants based on historical data obtained from [32], enabling us to quantify our modelling with respect to the reproduction of real-world market dynamics. In contrast to DRL strategies, we retain full transparency over the scheduling algorithms applied. Compared to game-theoretic approaches, our methodology offers superior performance. Second, our work provides a powerful enhancement to the open-source and state-of-the-art ABM AMIRIS[1] [33]. Specifically, all strategies described in this paper are openly available with AMIRIS. Therefore, AMIRIS is now not only highly capable for historical benchmarking simulations [34], but can also address future scenarios with high shares of renewable energies and competing FOs. Third, all presented benchmarking analyses are based on open data [35]. This enables users to reproduce our results and to conduct their own analyses in a convenient manner. In summary, we provide flexible and powerful algorithms to simulate competing energy storage units, and thereby contribute to a better understanding of current and future electricity markets.

The remainder of this paper is structured as follows. Section 2 outlines the fundamentals of the ABM AMIRIS. We present the individual storage strategies by describing their characteristics and potential applications. In Section 3, a case study is conducted to evaluate the performance of the presented storage strategies, both on an individual storage system level but also on the overall energy system level. We discuss our presented modelling approach in Section 4. Furthermore, we contrast our results with existing literature. Finally, in Section 5, we summarise our findings and offer suggestions on further research avenues.

2. Methods

To simulate the competition of energy storage units, we enhance the open *A*gent-based *M*arket model for the *I*nvestigation of *R*enewable and *I*ntegrated energy *S*ystems AMIRIS with powerful algorithms for dispatch planning and price forecasting. All of this is described in the following subsections.

[1] Agent-based Market model for the Investigation of Renewable and Integrated energy Systems.

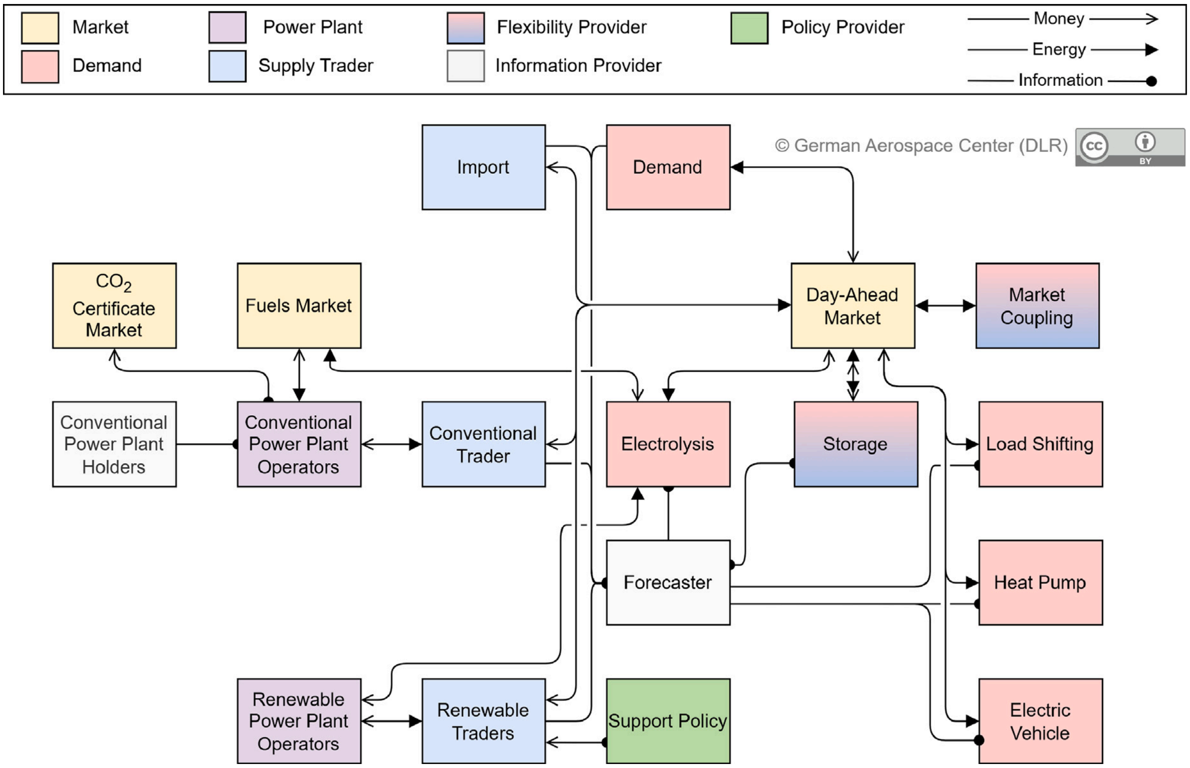

Fig. 1. Schematic representation of agent types and their interactions in AMIRIS version 3.7.2.

2.1. Electricity market modelling

AMIRIS is a comprehensive and powerful open-source tool [33] to model electricity markets. It has been designed to assist researchers in analysing complex challenges related to future energy market scenarios, market designs, and energy policy instruments. AMIRIS can simulate strategic bidding behaviour of various market actors, considering not just marginal prices but also the effects of support instruments, uncertainties, and market power [36]. Outputs comprise, e.g., electricity prices, dispatched energy as well as financial flows between the represented agents. AMIRIS is evolving constantly — results in this work were obtained with version 3.7.2 contained in the accompanying data release [35].

The structure of AMIRIS, depicted in Fig. 1, is based on seven main agent categories: markets, traders, power plant operators, demand agents, policy providers, forecasters, and flexibility providers. The day-ahead market performs the market clearing based on the bids provided by traders. Power plant operators generate electricity according to the market success of their corresponding trader. Demand agents buy energy from the day-ahead market, while policy providers influence the regulatory landscape and, in turn, affect the dispatch decisions of other agents [37]. Forecasts of electricity prices and of the merit order are provided by dedicated forecasters. Flexibility providers (energy storage, load shifting units, heat-pumps, electric vehicles, and electrolysers) utilise these forecasts to optimise their bidding strategy, thereby creating a dynamic simulation environment [14].

AMIRIS is based on the FAME framework [38,39]. The model has been applied to assess different FO technologies and concepts, such as Carnot batteries [40], battery storage systems [41], heat-pumps [11], demand response [42], and market coupling [43]. In this work, we enhance the forecasting method and the dispatch planning of energy storage units to simulate and assess their competition. Other FOs are disregarded. Each storage agent controls a single energy storage unit. Thus, the terms storage agent, storage operator, and storage unit can be regarded synonymous in this work.

2.2. Dispatch planning strategies

Dispatch planning strategies for storage agents in AMIRIS are determined by solving optimisation problems. We consider two strategy variants: one that maximises the storage agent's profits and one that minimises total system cost. These strategies facilitate analyses between maximum market power and full competition. The variants can easily be swapped for new simulations and even combined when using multiple storage agents. A cost-minimising strategy is often implicitly applied in energy system optimisation models which minimise the cost of the dispatch of all power plants [44] and also for power plant investments [45].

To find the optimal dispatch, AMIRIS storage agents use dynamic programming [46]. In this common solution approach, the storage unit's possible SOC is discretised in energy levels, and the time is discretised in time steps. This is illustrated in Fig. 2, where discretised energy levels are represented by stacked black lines which are repeated for each considered time step. Restrictions on the minimum and maximum SOC directly translate into available energy levels. The number of time steps is limited by the length of the foresight horizon. Starting at the last considered time step and progressing backwards, the value of each SOC level is determined by the value of the best possible transition to a follow-up level. This transition yields the best result for the sum of (i) the value of a potential follow-up level and (ii) the value of the transition to that level. Transitions are evaluated based on forecasts of the electricity price and the amount of electricity provided to or taken from the grid corresponding to the transition, see Section 2.3. Potential follow-up states are restricted by the maximum charge and discharge powers of the storage unit. Once the values and optimal transitions for all SOC levels and time steps have been assessed, the optimal path of SOC levels following the current energy level is determined in a forward pass. Since all potential follow-up levels must be checked for each SOC level, the computational cost scales quadratically with the SOC discretisation. To reduce computational overhead, we employ memoization techniques.

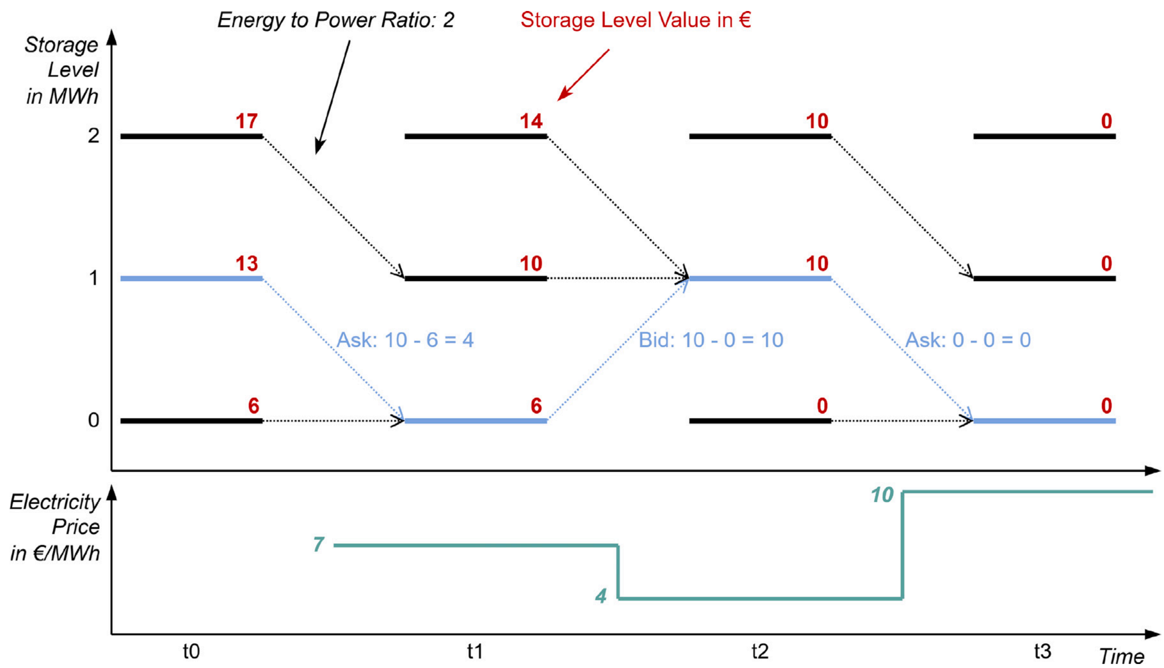

Fig. 2. Illustration of the dynamic programming algorithm and its bidding strategy for a storage with three SOC levels and three time steps (plus one for the initial state) with different electricity prices (green), not considering losses due to charging or discharging efficiencies; starting at a storage level of 1 MWh, the best path as well as related bid and ask prices are shown in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

In Fig. 2, the value of all storage levels is assumed to be zero in the last time step. This simplification neglects the value of storage at the end of the forecasting period, also known as water value (see e.g. [47]). To consider the value of storage at the end of the forecasting period, long-term simulations can be used to derive the water values. If such are not available, a rolling horizon approach with frequent reevaluations can be applied instead. Such approaches have been proven to yield good results for energy system modelling [48]. We also experienced the rolling horizon approach to yield good results if the E2P ratio of the storage unit is small compared to the foresight horizon.

The best path of SOC levels determines the amount of energy to sell to or to buy from the electricity market for every time step. To determine associated offer prices, we apply different rationales depending on the optimisation target. In case of system cost minimisation we want to ensure that the determined dispatch path is followed and use minimal or maximal allowed offer prices. When profit maximisation is employed we estimate the opportunity cost for changing the SOC level based on the previously determined SOC evaluations. For asks, the offer price P_t must compensate for the projected loss of value when moving from time t to $t+1$, which equals the difference between the estimated storage value V_{t+1} of the initial SOC level i and the final SOC level f, divided by the associated change in energy $\Delta E^{i,f}$:

$$P_t^{i\to f} = \frac{V_{t+1}^i - V_{t+1}^f}{\Delta E^{i,f}} \tag{1}$$

For bids, the offer price must not exceed the projected money that can be made from the additional energy, resulting in an exchange of initial and the final SOC levels i and f in Eq. (1).

Fig. 2 demonstrates all aspects of the algorithm with deliberately simple numbers. The storage device's SOC is discretised into three levels with 0, 1, and 2 MWh. Since the E2P ratio is two, the SOC can only change by 1 MWh per time step. Three time steps are considered, an additional fourth time step indicates the initial state of the storage device. As there is no water value considered here, the storage values (red numbers) are assumed to be zero for all SOCs in the last time step. Projected electricity prices change from 7 over 4 to 10 €/MWh. The best follow-up SOC levels are indicated by dotted arrows. An exemplary path starting with a half-filled storage is highlighted in blue. Bid and ask price calculations associated with the transitions are also shown in blue.

The outlined algorithm is well known but stands and falls with the electricity price forecast. For small amounts of installed storage, forecasts do not necessarily need to consider the feedback of storage dispatch on the electricity prices. This is assumed in Fig. 2. The dispatch of large or many storage devices, though, could have significant price impacts that potentially lead to avalanche effects. Thus, we also need to forecast price changes due to storage dispatch.

2.3. Forecasting

Electricity price forecasts used by AMIRIS agents are calculated based on three types of information for any respective time step: (i) What the electricity price would be without dispatch from storage agents, (ii) how the price would change with additional supply or demand, and (iii) how strongly the dispatch of a storage agent aligns with the dispatch of all competitors. In order to answer these questions, the forecaster agent collects preliminary bids and asks from the supply and demand agents for all future market clearing events within the foresight horizon. Without bids and asks of storage agents, the forecaster agent clears the market using the same algorithm as the day-ahead market agent to answer question (i). The resulting merit order is then inspected to assess how additional demand or supply from storages would change the clearing price. This "sensitivity forecast" answers question (ii). To answer questions (iii), we track the dispatch of all storage agents. For each time step, we calculate the total dispatch from storage agents as well as the share of each storage agent in this dispatch total. The inverse of this share represents an agent-specific multiplier to calculate the dispatch of all storage agents – including competitors – using the agent's own dispatch. This multiplier is rapidly changing over time and depends on the characteristics of the different storage agents. To achieve a more stable value, we average over multiple time steps. Based on the averaged "competition multiplier", each individual storage agent can estimate the future total dispatch of all storage agents using its own dispatch plans. By combining this approach with the

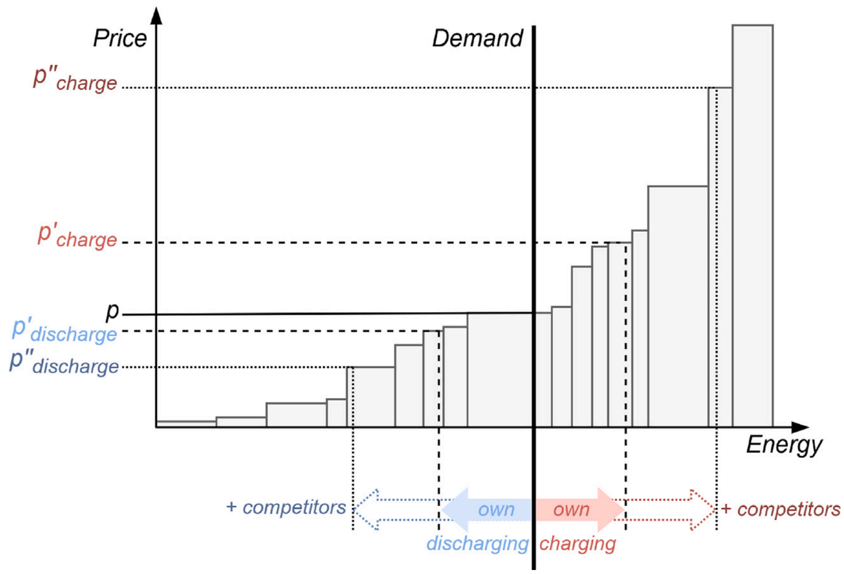

Fig. 3. Illustration of the interplay between merit-order forecasting and competition multipliers; without storage operations, price p is forecasted; based on the price sensitivity of the merit order (bar plot), storage agents can adjust the forecast to include their own dispatch (dashed lines) or even the dispatch of their competitors (dotted lines) resulting in new forecasted prices p' and p'', respectively.

sensitivity forecast each storage agent can estimate the total impact of all storage agents on future electricity prices.

Fig. 3 illustrates this mechanism using a schematic representation of the merit order. Without storage activity, the given demand and supply curves determine the price p. The forecast includes not only this price, but also how sensitive it is to changes in demand or supply. Thus, each agent can consider the impact of potential dispatch options on the electricity price p'. The impact of competitors on the prices p'' can also be considered using the competition multiplier.

At the beginning of the simulation, no information about the prior dispatch of the any storage agent is available. In order to provide a first estimate of the competition multipliers we utilise the theoretical dispatch potential of the storage agents, i.e., their charging and discharging capacities. In Eq. (2) we derive the initial multiplier estimates $m_{k,0}$ from the ratio of the total installed charging and discharging capacities C_j^{c} and C_j^{d} of all N storage agent j, relative to the installed charging and discharging capacities C_k^{c} and C_k^{d} of storage agent k.

$$m_{k,0} = \frac{\sum_{j=1}^{N}(C_j^{\mathrm{c}} + C_j^{\mathrm{d}})}{C_k^{\mathrm{c}} + C_k^{\mathrm{d}}} \tag{2}$$

Once dispatch data from previously simulated times is available, the unit-specific multipliers $m_{k,t}$ for each time t can be determined. Eq. (3) defines their calculation in a given time step using the net awarded energy $A_{j,t}$ of storage agents j.

$$m_{k,t} = \frac{\sum_{j=1}^{N} A_{j,t}}{A_{k,t}} \tag{3}$$

In order to calculate a moving average of unit-specific multipliers, we use an exponential smoothing of summands over time. This grants a higher attention to more recent values of the multipliers but also considers past values, albeit with less and less weight. Eq. (4) introduces the decay factor α based on the decay time constant τ. This constant represents the number of time steps after which the weight of a summand is reduced to about 37%.

$$\alpha = \exp(-\frac{1}{\tau}) \tag{4}$$

In order to blend smoothly from the initial estimate to the averaged ones, the initial estimate $m_{k,0}$ is granted an increased weight w_0. Eq. (5) represents the calculation of the averaged multiplier $\overline{m}_{k,t}$ for unit k at time t using the uni-specific multipliers from previous times t'.

$$\overline{m}_{k,t} = \frac{m_{k,0}\ w_0\ \alpha^t + \sum_{t'=1}^{t} m_{k,t'}\ \alpha^{t-t'}}{w_0\ \alpha^t + \sum_{t'=1}^{t} \alpha^{t-t'}} \tag{5}$$

With the calculation of the competition multiplier estimators, all forecasting data is compiled in the forecaster agent. The forecasted electricity price, its sensitivity on changes in demand and supply, and a competition multiplier estimator are distributed to each storage agent. These forecasts can then be applied by the storage agents to estimate the future electricity prices and thus values of stored energy for each potential dispatch path using dynamic programming as mentioned above.

This algorithm represents a high level of awareness for price impacts from competition. Other levels of awareness can be achieved by adapting the competition multiplier. If set to zero, no impact on the prices by the storage dispatch is assumed, resulting in the behaviour of a price taker. Price-maker behaviour is achieved with a competition multiplier value of one. This, however, is only consistent with a single storage unit in the system. In that case, the presented algorithm can provide perfect foresight, whereas in the case of competing storage units, competition multipliers are merely estimates.

3. Results

The following subsections compare the performance of the previously presented dispatch planning variants within a scenario based on the historical German wholesale electricity market of 2019. This backtesting scenario has been found to closely reproduce historical electricity market dynamics [34]. It was slightly enhanced with respect to the storage units. Additionally, we investigate a scenario with artificially increased storage capacities to demonstrate the dispatch strategies' capability to handle increasing competition. Important parameters are described in Appendix A. All data is openly available in the accompanying data release [35].

3.1. Single storage

We assess the price-taker and price-maker strategy variants first and aggregate the pumped hydroelectric storage units in the German electricity market into a single storage agent. We assess the ability of three

Table 1
Performance metrics for three variants of the storage dispatch strategy with one aggregated storage agent in the backtesting scenario; the sum of discharged energy is given in relative terms to historical dispatch. Profits are relative to a fictitious profit that would have been received from the historical dispatch at historical day-ahead market prices. The price-taker assumption leads to large overuse of storage and significant losses. Price-maker profit maximisation results in highest correlation with the historical prices but underuses storage capacities.

Metric	Profit maximisation price taker	System cost minimisation price maker	Profit maximisation price maker
Price correlation	0.62	0.80	0.87
MAE in EUR/MWh	8.76	6.21	5.09
RMSE in EUR/MWh	12.22	9.91	7.79
Dispatch correlation	0.80	0.75	0.68
Relative discharged energy	245%	149%	83%
Relative profits	−159%	70%	148%

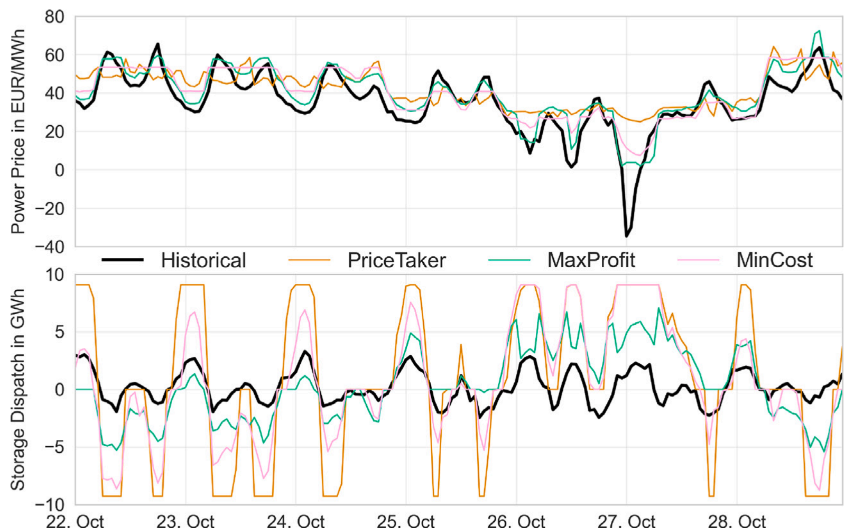

Fig. 4. Electricity prices resulting from simulation of storage dispatch with one storage agent in week 43 of the backtesting scenario using different strategy variants compared to the historical electricity prices (top); associated hourly storage dispatch from simulations and historical data (bottom)

dispatch strategy variants to explain historical electricity prices and storage dispatch. The first strategy variant applies profit maximisation but assumes to be a price taker, thus ignores the feedback of storage dispatch on electricity prices. The second and third variant apply a price-maker assumption and either aim to minimise the system cost, or to maximise their profits. Each strategy variant is tested in its own simulation without any competitors.

Table 1 compares the Pearson correlation of the simulation results with the historical day-ahead market prices, as well as the associated mean absolute error (MAE) and root mean square error (RMSE). Additionally, it shows the Pearson correlation of the simulated storage dispatch with the historical storage dispatch, the cumulative simulated discharged electricity relative to the historical storage discharge, as well as the profits obtained in the simulation relative to those that would be achieved with historical prices and dispatch. Historical data were obtained from [32].

With the AMIRIS electricity price forecasting mechanism (see Section 2.3), single storage agents can be provided with perfect information and market power. The price-taker variant forfeits this market power and assumes that its dispatch has no impact on the prices. While this results in the highest Pearson correlation with historical dispatch, correlation with the prices, as well as MAE, and RMSE are the worst among the variants due to massive overuse of the storage. Fig. 4 shows this effect. It displays one week of simulated dispatch and the resulting electricity prices alongside the historical dispatch and prices. With the price-taker variant, expected price valleys and hills are often flattened or even inverted, resulting in negative profits. Unsurprisingly, this emphasises the need to consider the price feedback of storage dispatch.

Similar to the price-taking variant, the system-cost minimisation variant also involves the overuse of storage capacities compared to the historical reference — but to a lesser degree. Here, perfect foresight of the impact of dispatch on prices is available and market power is used to avoid price inversions. Thus, price spreads are merely reduced. The correlation with the historical price is strong with a value of 0.8, and the MAE and RMSE are significantly better than in the price-taker variant. However, the correlation with historical dispatch is slightly reduced, and only 70% of profits are generated compared to the historical dispatch.

The profit-maximisation variant also uses perfect foresight and market power, which results in a reduction of total storage dispatch to maintain profit-optimal price spreads, i.e. to avoid self-cannibalisation of profits. This leads to the highest correlation of simulated and historical prices with lowest MAE and RMSE. With 148% of the fictitious reference value, profits are significantly higher than what could be expected from the historical dispatch.

In contrast, Fig. 4 shows that, for the profit-maximising variant, too few capacities are utilised. The correlation with the historical dispatch is the lowest among the variants. This shows, that the assumption of perfect information combined with high market power leads to unrealistic dispatch restraints and overestimation of profits when applied to a single storage agent.

It is important to interpret the comparisons of historical and simulated prices and dispatch in Figs. 4 and 6 (further below) with caution. Even if the storage units in the model reproduced the historical dispatch exactly, AMIRIS would not be able to perfectly replicate historical electricity prices. There are several reasons for this. Historical storage dispatch is influenced not only by day-ahead market outcomes but also by activity on intraday markets and reserves markets. In contrast, our AMIRIS simulations cover only the day-ahead market, thus bidding behaviour of actors is not perfectly reproduced. Furthermore, the

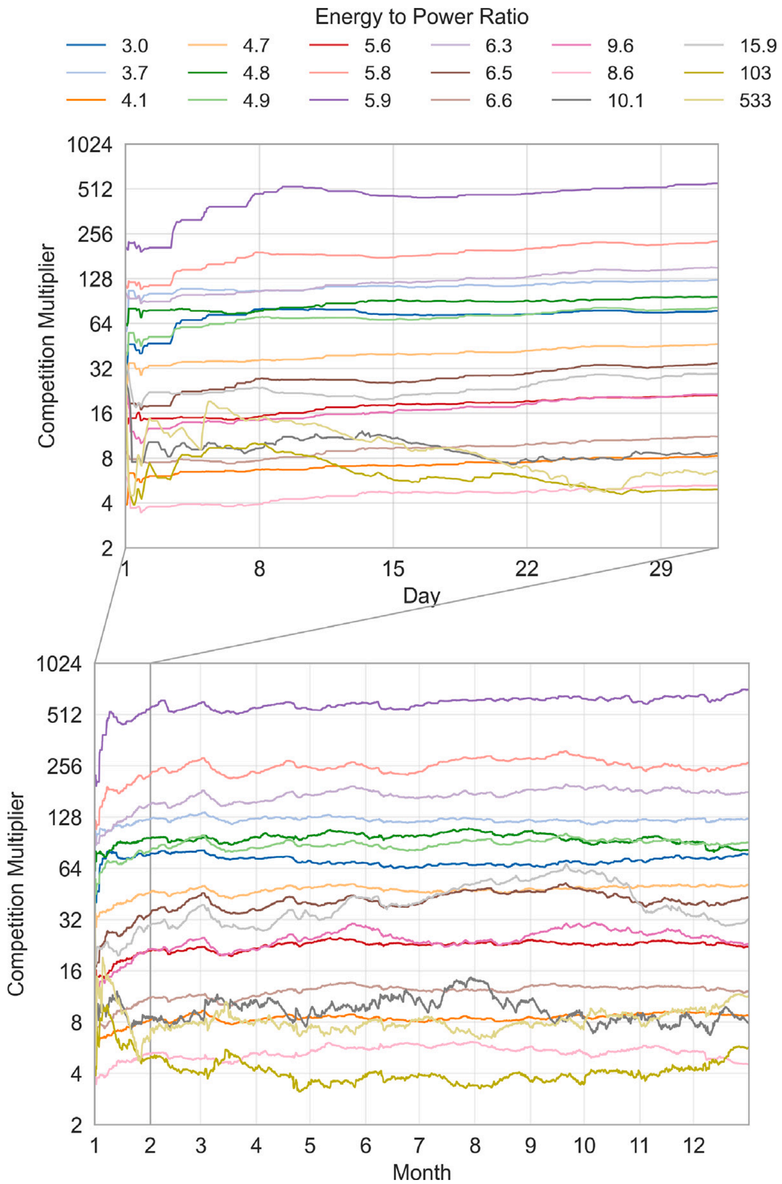

Fig. 5. Averaged multipliers over the full simulation year (bottom) and in detail for the first month (top) for 18 competing storage units with varying E2P ratio using a profit maximising dispatch strategy; initial estimate weight $w_0 = 6$, decay time constant $\tau = 168$ hours.

shown AMIRIS simulations do not include transmission constraints or redispatch. In reality, these aspects can significantly alter the dispatch of units. Additionally, agents in AMIRIS operate with less uncertainty than real-world actors, who must deal with imperfect forecasts and unpredictable market behaviour. Lastly, there are simplifying assumptions in the backtesting scenarios. For example, the scenario relies on hourly market clearing, approximate power plant efficiencies, estimated power plant availability profiles and stylised must-run constraints.

3.2. Competing storages

We assess the performance of the developed dispatch planning and forecasting algorithm regarding the modelling of competition. To this end, we simulate 18 competing storage agents and employ the aforementioned three storage dispatch strategy variants within the otherwise same backtesting scenario. Total storage power and capacity of the 18 pumped-hydro storage units is identical to that of the single storage unit in the previous section. Only units with similar round-trip efficiency (RTE) and E2P were aggregated. Details regarding the parametrisation of the storage units are provided in Appendix A.

3.2.1. Competition multiplier estimates

The competition estimation process outlined in Section 2.3 contains two soft parameters, the initial weight w_0 and the weight decay time τ. These can affect the performance of the storage units. If w_0 is too small, the competition multiplier estimates show strong fluctuations at the beginning of the simulation. If w_0 is too large, the measured multiplier data is suppressed for a longer time span. The decay time τ can be compared to the averaging window of a moving average. If it is chosen too small, fluctuations increase, but if it is chosen too large, adaptations take too long. To identify a combination for w_0 and τ with stable performance we conducted a parameter study and identified $w_0 = 6$ and $\tau = 168$ hours as a good combination. The results for price correlation, dispatch correlation, and profitability were extremely stable over the assessed parameter ranges. Details of the parameter study are shown in Appendix B.

Fig. 5 shows the development of competition multiplier estimates for 18 competing storage units during a simulated year. For most of the storage units, the multiplier estimates stabilise after one week. The storage units whose multipliers take the longest to stabilise are those with the highest E2P ratio. The selected decay time of 168 h enables

Table 2
Performance metrics for three variants of the storage dispatch strategy with 18 competing storage agents in the backtesting scenario year; discharged energy totals are relative to historical dispatch. Profits are relative to a fictitious profit that would have been received from the historical dispatch and historical day-ahead market prices. Compared to single-agent representation, total discharged energy is reduced while dispatch correlation and MAE improve for all strategy variants.

Metric	Profit maximisation price taker	System cost minimisation competition estimate	Profit maximisation competition estimate
Price correlation	0.66	0.85	0.87
MAE in EUR/MWh	8.46	5.37	5.24
RMSE in EUR/MWh	11.93	8.12	7.83
Dispatch correlation	0.87	0.86	0.79
Relative discharged energy	222%	107%	72%
Relative profits	−161%	109%	129%

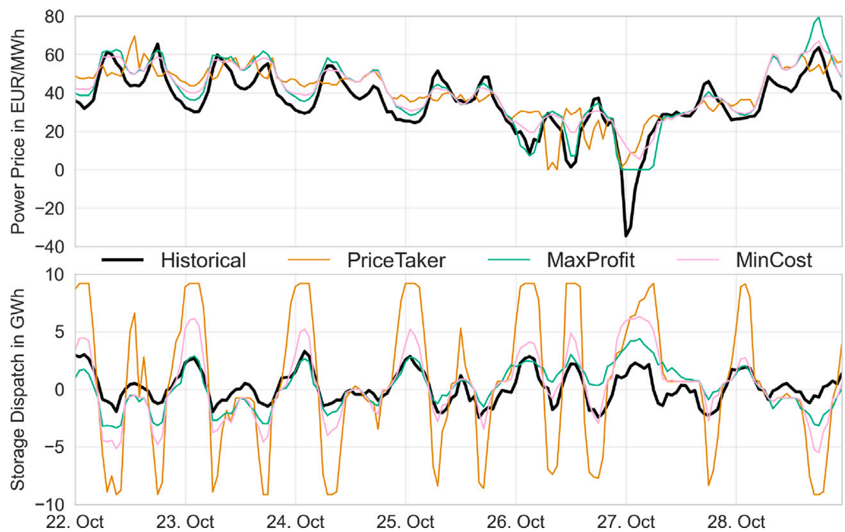

Fig. 6. Electricity prices resulting from simulation of storage dispatch with 18 competing storage agents in week 43 of the backtesting scenario using different strategy variants compared to the historical electricity prices (top); associated hourly storage dispatch from simulations and historical data (below).

mid-term adaptions of the competition multipliers due to changed market situations while providing short-term stability. To assess whether the initial estimates for the competition multipliers are reasonable, we compare them to the averaged competition multipliers at the end of the simulation. We find that the initial multiplier estimates are off by less than a factor of 4. This correction factor of the initial estimates has a Pearson correlation of −0.9 with the RTE. Therefore, competition multipliers for storages with high RTE are initially overestimated, and those for storages with low RTE begin underestimated. This can be explained by a number of dispatch opportunities that can only be exploited with high RTE, but increased competition in situations with high price spreads.

3.2.2. Backtesting performance

Table 2 shows the performance metrics associated with 18 competing storage agents in the backtesting scenario. Compared to the single-agent representation, the multi-agent representation improves performance with respect to the price and dispatch correlations. MAE and RMSE improve for the price-taker and system-cost minimisation variants, but slightly worsen for the profit-maximisation variant. Total discharged energy is reduced in all cases, as the developed algorithm only provides a good, not a perfect, estimate of the competitors' behaviour. This reduction brings the profit and the sum of dispatched energy of the system-cost minimisation variant close to the historical results.

Fig. 6 shows the cumulative hourly dispatch from all storage units and associated electricity prices for the three dispatch strategy variants against historical data for the same week as in Fig. 4. Several differences can be spotted when comparing these two figures. These differences are caused by the disaggregation of storage capacity into distinct units with specific RTE and E2P ratios, as well as the added uncertainty from competition. Results for the price-taker variant exhibit slightly reduced charging and discharging peaks. However, the high-efficiency storage units are overused and additional charging and discharging activities lead to additional peak–valley inversion events of the electricity price on the fifth day. The system-cost minimising and profit-maximising variants show less pronounced charging and discharging peaks, and are more closely related to the historical dispatch.

Fig. 7 shows the same week as Fig. 6 but depicts the individual dispatch of three storage units with the profit-maximising strategy variant. The storage units differ strongly with respect to their technical parameters, causing different dispatch patterns. It can be seen that the most active unit is that with the highest RTE (purple). This unit charges and discharges for several hours each day, while the unit with the lowest RTE (green) can barely exploit any of the small under-the-day price spreads. The high-efficiency unit performs both charging and discharging activities between October 25th and 27th, whereas the unit with largest E2P (orange) utilises its storage capacity for charging only. In this way, it can exploit the relatively low prices at that time compared to those during the first three days of the following week (not shown).

3.3. Increased competition

The impact of competition increases with higher storage capacities. To demonstrate the applicability of the presented method to highly competitive scenarios, we deviate from the backtesting scenario and

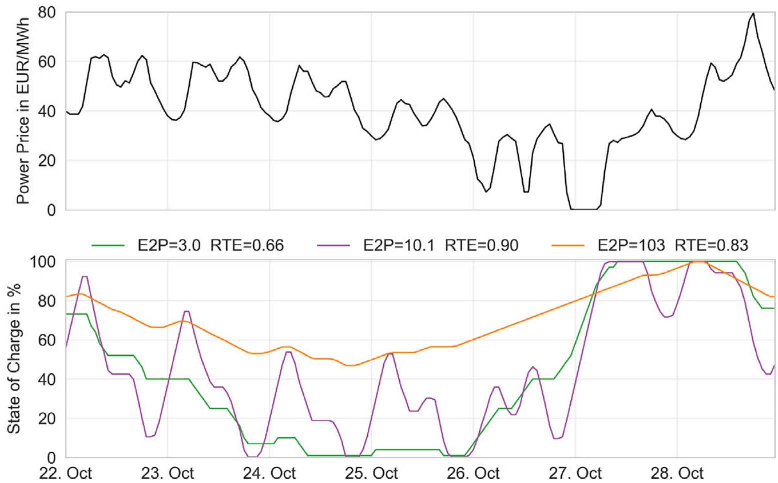

Fig. 7. Electricity prices resulting from the simulation of storage dispatch with 18 competing storage agents in week 43 of the backtesting scenario using the profit-maximising dispatch variant (top); state of charge for three storages units with different energy-to-power ratios and round-trip efficiencies (bottom).

Table 3
Power, capacity and round-trip efficiency of storage units added to the backtesting scenario; unit identifiers are equal to their energy-to-power ratio. The same round-trip efficiency is assumed for all additional storage units.

Storage unit identifier	Converter power	Storage capacity	RTE
Battery 1	5 GW	5 GWh	0.865
Battery 2	5 GW	10 GWh	0.865
Battery 3	5 GW	15 GWh	0.865
Battery 4	5 GW	20 GWh	0.865

Table 4
Discharged energy and profit totals of 18 competing storage units in the backtesting scenario and the scenario with increased storage capacity using either cost-minimising or profit-maximising strategies; with system cost minimisation, storage capacities are strongly used, thus reducing profits. Profit maximisation shows a moderate increase of storage usage, and a small increase of storage profits.

Metric	Scenario	System cost minimisation	Profit maximisation
Discharged Energy Total in TWh	Backtesting	7.32	4.95
	Increased Capacity	10.71	6.61
Total Profits in M€	Backtesting	105.3	124.2
	Increased Capacity	75.4	137.8

increase the amount of installed storage by 20 GW. Motivated by recent developments in Germany, we concentrate on short-term storage that resembles, e.g., batteries. We consider 5 GW additional capacity, each for E2P ratios of 1, 2, 3, and 4. All additional units are assigned a similar RTE. Table 3 shows the parameters of the additional storage units.

We evaluate both the system-cost minimising and profit-maximising dispatch strategy variants for the case of 18 competing storage agents. Due to the changed scenario setup, we do not compare with historical data. Instead, we compare with the original backtesting scenario to assess the impact of the additional storage units. Table 4 highlights the absolute profits and discharged energies in both scenarios and for both dispatch strategy variants. In case of system-cost minimisation, the additional units are strongly put to use and the discharged energy total rises from 7.3 TWh in the backtesting scenario to 10.7 TWh in the increased capacity scenario. This, however, reduces the total profit from 105 M€ to 75 M€, due to price spread dampening (see below). With the profit maximisation strategy variant, the discharged energy total moderately increases from about 5 TWh to 6.6 TWh in the increased capacity scenario due to the higher-than-average efficiency of the additional units. The total profit increases as well, but only from 124 M€ to 137 M€.

As Fig. 8 shows, the profit-maximising dispatch strategy variant (green colours) creates very similar prices in the backtesting scenario and the additional capacity scenario. This strategy variant restricts the use of additional storage power and capacity to maintain higher price spreads. However, the system-cost minimising dispatch variant (pink colours) uses the additional capacities especially at the beginning of the shown week to further reduce the differences between price minima and maxima when compared to the backtesting scenario. For reference, we also provide prices from a scenario without any storage units (grey colour) to demonstrate the storage units' price impact.

Fig. 9 compares the installed converter power and storage capacity of the original backtesting scenario with that of the additional battery storage units. Although the newly installed battery storage units account for more than triple the converter power, the total installed storage capacity is only increased by about 20%. Since the system-cost minimising dispatch strategy variant produced a dispatch closest to the real-world (see above), we assess this strategy here. Due to the higher RTE of the additional battery units compared to the existing pumped-hydro storage units, the battery units generate about 52% of the profits and provide 59% of the dispatched energy.

4. Discussion

We tested variants of storage dispatch strategies with different optimisation targets and varying awareness of price impacts from storage

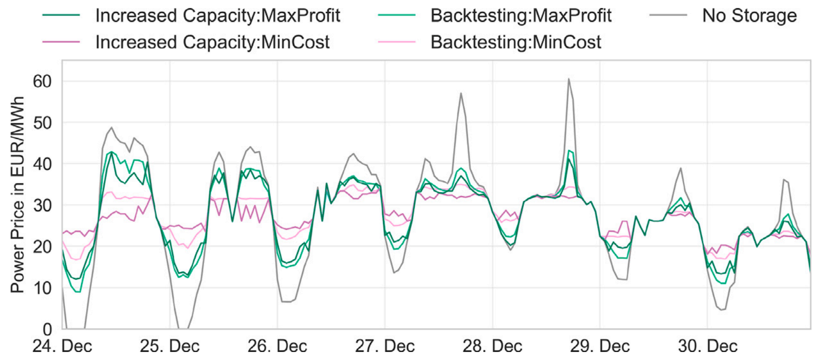

Fig. 8. Electricity prices in the last week of a scenario without any storage units (grey), of the backtesting scenario (light colours), and of the scenario with increased storage capacity (dark colours) for cost-minimising (pink) and profit-maximising (green) strategy variants. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

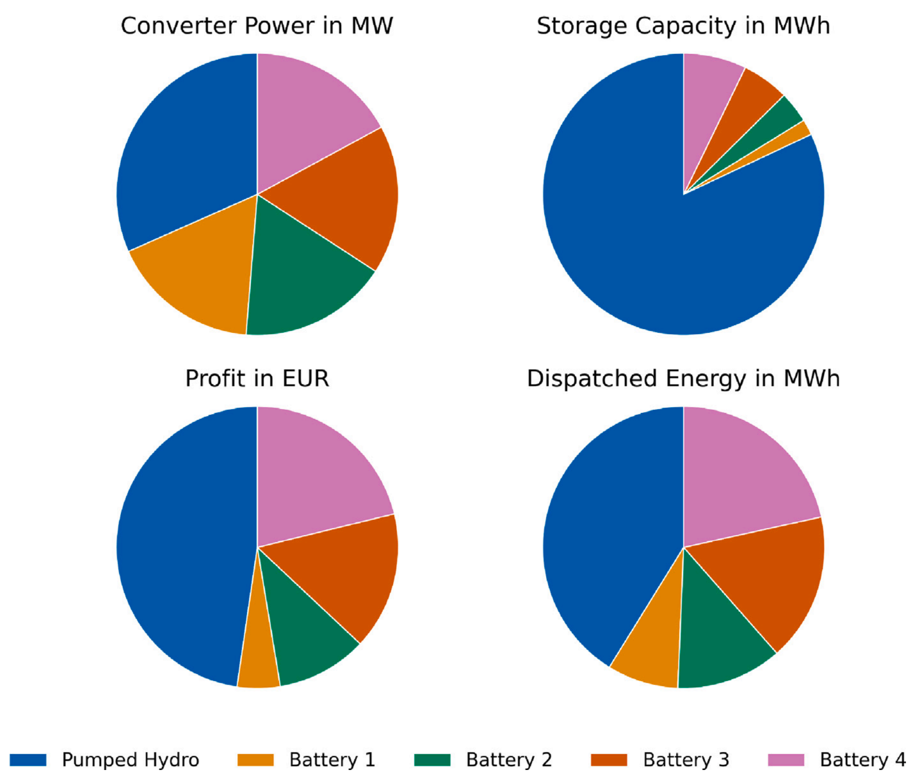

Fig. 9. Scenario with extended storage; share of installed converter power and storage capacity with sum of original pumped-hydro storages in blue (top); share of profits and dispatched energy between newly installed units in pink, brown, green, and gold as well as the corresponding total of all original units in blue using the system-cost minimising dispatch variant (bottom). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

dispatch. For both, a single large storage unit and disaggregated storage units, we observed significant overuse of the storage units if these are not aware of their price impacts. Therefore, price-taker dispatch strategies should be combined with predictions that already include an expected impact of storage units on the price. This can make performative predictions necessary [49] that consider the impact of electricity price predictions on the simulation outcome [14].

With a single storage unit that is perfectly aware of its own price impacts, price-maker behaviour is found. When combined with the optimisation target of system cost minimisation, results are equivalent to those of a global cost minimisation model [50]. Employing the optimisation target of profit maximisation, though, can illustrate the impact of market power on profits and strategically reduced dispatch. This also leads to higher system cost [50].

To simulate competition, the developed algorithm estimates multipliers resembling the effective combined storage power. This allows to approximate the impact on electricity prices from all competitors and to avoid avalanche effects. The multipliers are individually adapted for each storage unit to consider the impact of different E2P and RTE characteristics. This approach aligns the dispatch of the storage units, by letting them assume that the dispatch of competing storage units will correlate with their own dispatch. In case of the profit-maximising strategy, this presumed dispatch alignment strongly restricts storage usage in order to increase profits. This corresponds to collusion which is also found in other studies assessing the effects of coordinated storage behaviour [26]. However, when applied with a cost-minimising strategy, the dispatch alignment of individual storage units also prevents their overuse, but to a lesser extent and similar to a global cost-minimisation. Thus, the alignment aspect of the algorithm in this case simulates the outcome of (almost) perfect competition. When compared with the historical dispatch of storage units, we find higher coincidence levels of the simulated dispatch when applying a cost-minimising strategy. This could mean that real-world storage units do not utilise significant market power and that the German electricity market was close to perfect competition with insignificant collusion of storage units in the assessed year. This implication, however, is to be taken with a grain of salt, since other aspects can impact storage operation as well, most prominently the participation in intra-day and reserve markets.

Despite its similarity to energy system optimisation models, our presented approach allows to combine different optimisation rationales for multiple agents. Thus, partial market power could be simulated. Additionally, the interplay between competing storage systems and other market designs, such as renewable energy remuneration policies [51], can be studied using this approach. Furthermore, it can easily be enhanced to consider the individual prediction uncertainties of different storage operators.

In comparison to ABMs that employ machine-learning to model storage competition, such as [14] and [28], our approach provides superior computational performance as there is no training required. Instead, our algorithm's soft parameters, initial weight and decay time constant (see Section 2.3), proved to yield stable results over a wide range of the parameter space (see Appendix B). This indicates that the default parameters can probably be used without adaptation for a wide range of scenarios. Additionally, the employed dynamic programming algorithm yielded good results during execution, even with a quite coarse energy resolution of one tenth of the converter power per storage unit. The average runtime for scenarios with 18 competing storage units for a full year with hourly resolution was about 30 seconds per simulation on a personal computer (Intel Core i7-1370, 32 GB of Memory). A performance test with 1 to 128 storage agents is shown in Appendix C. It demonstrates that our approach scales linearly with the number of storage agents included in simulations and thus enables large-scale parameter studies, even on limited hardware. While providing other benefits, equivalent case studies of ABMs utilising machine learning to model storage competition, demonstrate training times in the range of hours [52] on the same machine.

An additional benefit of the presented implementation is that it allows to quantify the lower and upper limits of storage profitability by switching between the two implemented optimisation rationales of cost-minimisation and profit-maximisation. The cost-minimisation rationale provides a "perfect competition" estimate and acts as a lower boundary for system costs and storage profits. The profit-maximisation rationale, on the other hand, demonstrates collusion among storage units and thus represents an equivalent upper boundary to those quantities. However, it implies that market actors employ similar algorithms for price forecasting, competition estimation, and dispatch planning. In case historical dispatch information is published a few hours after real time, such collusion behaviour could theoretically be realised by actual market actors. For the German market, corresponding data is available [32]. Thus, in order to prevent the abuse of collective market power, antitrust regulations might be necessary. At least, the dispatch behaviour of storages and other flexibility options should be monitored.

To showcase the capability of our algorithm to deal with higher levels of competition, we increased the total storage power in a stylised scenario. Depending on the dispatch strategy variants, we observed only a moderate increase of total profits for storage units at best, or even a significant reduction. In general, such studies could contrast technology-specific economic assessments that rely on historical price projections, e.g. [53]. However, our stylised evaluation did not consider an increase of renewables in the scenario. These would likely increase the price spreads and thus present additional dispatch opportunities for storage units. We expect storage profits in such a scenario to be highly dependent on the competition with other flexibility sources, such as flexible loads, increased international trading, flexibility from sector coupling technologies, e.g. electrolysers, heat pumps or electric vehicles. In Germany, compared to the detailed expansion pathway goals for variable renewable generators defined in the German renewables act [54], there is no overall goal concerning the capacity pathway of flexibility sources. There are some strategic policy goals, such as installing at least 500,000 heat pumps per year and reaching 15 million electric vehicles by 2030 [55]. However, these goals are not binding and, for the case of heat pumps, have been failed in the past years. In contrast, there is a large uncertainty about how the capacity mix will evolve and influence remuneration perspectives of storages. This might change with the obligation of introducing indicative flexibility goals for EU member states according to Article 19f of [56]. Furthermore, we did not consider other revenue streams for storage units from, e.g., intraday markets or peak shaving, as illustrated in [57]. These activities would likely influence the simulated dispatch and, ultimately, the modelled electricity prices, depending on how storage units optimise across multiple markets simultaneously. Also, we did not account for revenue streams from policy instruments that are subject of debate, but not yet introduced. Relevant policy instruments could be flexibility markets or capacity remuneration mechanisms, which by EU law must be open to storages or flexible loads according to Article 22 of [56]. The latter can even be combined with dedicated revenue streams from support mechanisms for non-fossil flexibility according to Article 19 g and 19 h of [56]. Those additional revenue streams could impact bidding behaviour in day-ahead markets and consequentially affect dispatch patterns and storage profits.

Comparing with other approaches as presented in [58], our method incorporates strategic behaviour of storage units, but is not based on an equilibrium approach. While granting high computational efficiency and the possibility to include uncertainty into decisions, our method lacks mathematical proof. A comparison of the results for single and multiple storage units indicates that our approach of competition modelling is at least plausible. Still, a direct comparison with game-theoretic models would be necessary to strengthen trust in the presented approach.

5. Conclusions and outlook

We developed an algorithm for dispatch scheduling of competing storage units based on dynamic programming and smart electricity price forecasting. The algorithm and its variants were integrated in the agent-based electricity market model AMIRIS. We used a back-testing scenario of Germany to compare profit-maximising and system cost-minimising dispatch strategy variants. Furthermore, we applied aggregated and disaggregated representations of the storage units to assess the dispatch strategies with respect to avalanche effects, market power and competition. A scenario setup with additional battery storage units demonstrates the applicability of our approach also for highly competitive situations.

Results for the price-taker strategy variant highlight the risk of avalanche effects when price impacts due to storage dispatch are not considered. Such avalanche effects can be avoided with our presented algorithm that allows to equip agents with the necessary awareness of storage units' price impacts. This has been proven to work with single or multiple competing storage units. It was shown that the simulation of competing storage units can improve model quality with respect to the reproduction of historical dispatch behaviour. The profit-maximising strategy variant produced the best results when modelling historical electricity price dynamics but seems to overestimate profits and underestimate the storage usage. Metrics of the system-cost minimising variant improved the most due to the disaggregated representation of storage units. With this variant, storage profit and dispatch were closest to historical market results. This aligns with market theory expectations that in highly competitive systems fewer market power is prevalent [59].

In summary, our method allows to incorporate storage competition into agent-based simulations using a transparent and understandable dispatch planning approach. It enables researchers and decision-makers to assess the market dynamics of competing storages within imperfect

Table A.1
Technical and economical parameters of conventional power plants.

Technology	Installed Capacity in MW	Block Size in MW	Efficiency Minimum in %	Efficiency Maximum in %	Variable OPEX in €/MWh	Markup Minimum in €/MWh	Markup Maximum in €/MWh
Nuclear	9524	900	33.0	33.1	0.5	−150	−90
Lignite	21,067	500	31.1	45.0	2.0	−60	0
Hard coal	22,458	300	33.9	49.2	2.5	−15	5
Natural gas CCGT	13,572	200	51.6	61.7	1.2	−10	10
Natural gas OCGT	13,206	100	32.7	44.9	1.2	10	50
Oil	3934	100	31.1	39.7	1.2	0	0

Table A.2
Average prices and CO_2 emissions of different fuels.

Fuel	Average price in EUR/MWh	CO_2 in kg per thermal MWh
Nuclear	2.0	0
Lignite	5.0	364
Hard coal	10.98	341
Natural gas	16.67	201
Oil	37.08	264

markets, where policy impacts and uncertainties are also considered. Since we base our analyses on open source modelling and open data, the algorithm and its results are fully replicable.

Still, there are several opportunities for further research and development. Firstly, extending the analysis to include multi-market respectively multi-use scenarios, such as intraday markets, peak shaving or ancillary services, will provide a more thorough understanding of how flexibility options can be optimised across different market contexts. Secondly, further technical storage details could be added to the assessment, including the degradation of storage systems or self-discharge rates, in order to enhance the accuracy of the operational simulations. Thirdly, an important next step would be to validate the robustness of the presented approach with respect to other market situations, e.g., by expanding the analysis to further historical years. Especially the years 2020 to 2024 could serve as an acid test for the approach due to the harsh changes in market conditions in those years, e.g., from changing demand patterns and natural gas prices. Furthermore, comparisons with reinforcement learning models and game-theoretic models could provide a more comprehensive evaluation of the strategic interactions among various market participants. Quantitative comparisons with these model types are required to further substantiate the indicated benefits of the presented approach regarding performance, scalability, and accuracy. Last, the developed dispatch planning algorithm could be extended to cover other FOs, e.g., heat pumps, electrolysis units, or mobility and load shifting applications. Pursuing these avenues would create a more informed basis for designing policy and regulating markets, enabling robust simulations of highly renewable energy systems.

Glossary

ABM agent-based model

DRL deep-reinforcement learning

E2P energy to power

FO flexibility option

MAE mean absolute error

RMSE root mean square error

RTE round-trip efficiency

SOC state of charge

CRediT authorship contribution statement

Christoph Schimeczek: Writing – original draft, Validation, Software, Methodology, Data curation, Conceptualization. **Felix Nitsch:** Writing – original draft, Validation, Software, Methodology, Data curation, Conceptualization. **Johannes Kochems:** Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Kristina Nienhaus:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Backtesting scenario

Here, we provide the most important parameters for the backtesting scenario and its variants. The scenario is based upon a scenario of the German day-ahead electricity market in the year 2019 [60]. All data are openly accessible [35].

Technical and economic parameters of conventional power plants are shown in Table A.1. Installed capacities are split into blocks of specified size. Unit efficiencies are interpolated between the specified minimum and maximum. Mark-downs or markups are also interpolated per unit between the specified minimum and maximum. High (low) markups or mark-downs are assigned to units with low (high) efficiency. Variable operation expenditures (OPEX) are assumed per thermal MWh and otherwise constant per technology. Natural gas power plants are split into open and closed cycle gas turbines (OCGT, CCGT). Cost and emission parameters of associated fuels are shown in Table A.2. Technical and economical parameters of renewable power plants are shown in Table A.3. Renewable capacities are not split into units, but chunks with same remuneration parameters. Most capacities are bound to a remuneration scheme, of which feed-in tariffs (FIT) and variable market premia (MP) are used.

Significant effort was put into the compilation of an accurate parametrisation for the storage units since [61] do not cover pumping power or reservoir capacities and have only very rough estimates for round-trip efficiency. Regarding the storage units in Germany, we derived installed charging and discharging powers as well as storage capacities from [62]. For round-trip efficiencies we combined age data of the storage from [61] with efficiency data from [63]

Table A.3
Technical and economical parameters of renewables power plants.

Technology	Installed capacity in MW	Variable OPEX in €/MWh	Remuneration schemes
Photovoltaics	47,753	0	FIT, MP
Wind onshore	53,553	0	FIT, MP
Wind offshore	7504	0	MP
Run of River	5268	0	FIT
Biogas	7833	0	–
Other Renewables	454	1.2	–

Table A.4
Technical parameters of the aggregated and disaggregated (1-18) storage units; Charging and discharging powers refer to the maximal grid interaction. Storage capacities refer to the internally stored energy (after application of the charging efficiency, before applying discharging efficiency).

Unit	Charging Power in MW	Discharging Power in MW	RTE in %	Capacity in MWh
Aggregated	9188	9325	76.8	227,731
1	400	370	66.0	1,147
2	153	165	76.5	590
3	2340	2336	74.3	9,470
4	360	358	76.0	1,725
5	143	145	80.0	693
6	231	219	71.2	1,103
7	661	623	77.5	3,584
8	80	80	69.6	460
9	46	43	59.8	264
10	90	90	74.8	563
11	463	457	70.0	2,990
12	1078	1002	77.4	6,823
13	327	493	76.7	3,950
14	1540	1532	80.7	13,235
15	360	360	90.3	3,650
16	242	289	74.0	4,234
17	450	525	82.8	50,050
18	224	238	82.8	123,200

plus own estimates, and compared the results with [64]. We also included five storage units in Austria connected to the German grid. Their charging and discharging powers as well as storage capacities were taken from [65]. We estimated round-trip efficiencies based on water flows during charging and discharging. Regarding the single storage unit in Luxembourg, we used data from their website. Table A.4 shows technical parameters of the aggregated and disaggregated storage units. In both scenarios, initial state of charge for all storage units was about 43 %. In total, 28 individual storage units with installed converter power above 30 MW were considered. These were either aggregated into a single unit, or 18 units. In the latter case, only units with very similar round-trip efficiency and energy-to-power ratio were aggregated. For the aggregation, we added up the charging powers, discharging powers, and storage capacities of the individual units. Regarding the round-trip efficiencies, we applied an average weighted by the converter power.

Appendix B. Soft parameter study

The soft parameters w_0 and τ were introduced in Section 2.3. These parameters determine the estimation of the competition multipliers. As mentioned in Section 3.2.1, the choice of these parameter can impact the performance of competing storage units: If w_0 is too small, the competition multiplier estimates show strong fluctuations at the beginning of the simulation. If w_0 is too large, the measured multiplier data is suppressed for a longer time span. The decay time τ can be compared to the averaging window of a moving average. If it is chosen too small, fluctuations increase, but if it is chosen too large, adaptations take too long. However, there is no strict way to deduce the best value for these parameters. Therefore, we conducted a parameter study of w_0 and τ to identify a parameter combination that yields good results for

Table B.1
Correlation of electricity prices with historical prices in the backtesting scenario for 18 storage units and variations of w_0 and τ; higher values of τ yield a slightly higher correlation. The lowest (highest) correlation is marked in cyan (magenta) colour.

τ/w_0	1	3	6	12	24
48	0.8665	0.8662	0.8667	0.8665	0.8666
96	0.8668	0.8664	0.8666	0.8667	0.8668
168	0.8668	0.8669	0.8669	0.8669	0.8669
336	0.8668	0.8668	0.8672	0.8671	0.8674
730	0.8672	0.8672	0.8674	0.8676	0.8675

Table B.2
Correlation of total dispatch from 18 storage units with historical dispatch in the backtesting scenario for variations of w_0 and τ; lower values of w_0 yield a slightly higher correlation. The lowest (highest) correlation is marked in cyan (magenta) colour.

τ/w_0	1	3	6	12	24
48	0.7891	0.7886	0.7888	0.7879	0.7887
96	0.7895	0.7886	0.7893	0.7885	0.7892
168	0.7895	0.7886	0.7884	0.7886	0.7884
336	0.7892	0.7886	0.7876	0.7880	0.7876
730	0.7896	0.7888	0.7885	0.7876	0.7872

Table B.3
Total profit of 18 storage units relative to fictitious profits that would result from the historical dispatch at historical day-ahead market prices the in the backtesting scenario for variations of w_0 and τ; larger values of w_0 and τ yield slightly better profits. The lowest (highest) profit is marked in cyan (magenta) colour.

τ/w_0	1	3	6	12	24
48	128.5%	128.6%	128.6%	128.6%	128.7%
96	128.8%	128.8%	128.8%	128.8%	128.8%
168	128.8%	128.8%	128.8%	128.7%	128.7%
336	128.9%	129.0%	129.0%	129.0%	129.0%
730	129.2%	129.3%	129.3%	129.3%	129.3%

the storage competition. Furthermore, the parameter study can indicate how sensitive the results are with respect to the choice of the two parameters.

Overall, results for price correlation (Table B.1), dispatch correlation (Table B.2), and profitability (Table B.3) are very stable over the assessed parameter ranges. The difference between the best and worst value for price correlations differs by 0.0014, which corresponds to a relative difference of 0.2%. Similarly, the best and worst value for dispatch correlations are 0.0024 apart, corresponding to a relative difference of 0.3%. Profitability values vary by up to 0.0077. This corresponds to a maximum relative change of 0.6%. Best values for price correlation and profitability can be found at high values of w_0 and τ, whereas best values for dispatch correlation are located at low values of w_0 and τ. However, the sensitivity of the results on the choice of w_0 and τ is so weak, that this choice has no relevant impact on the results presented in Section 3.

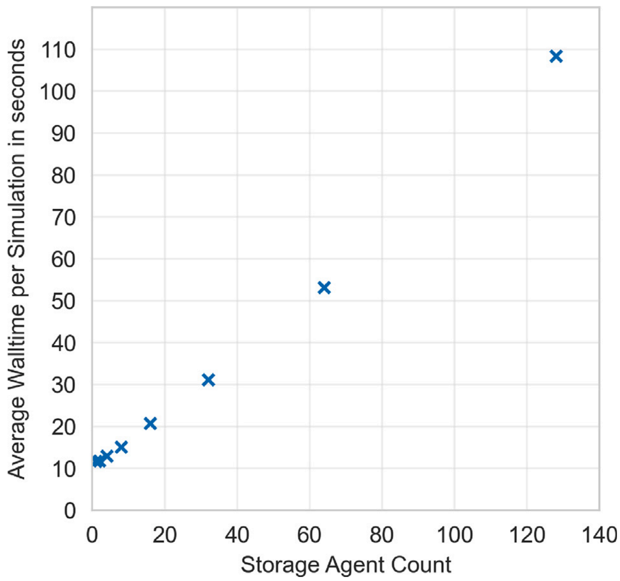

Fig. C.1. Average walltime of a simulation depending on the number of storage agents; the walltime scales approximately linearly with the number of storage agents.

Appendix C. Performance benchmark

The optimisation of storage dispatch using dynamic programming scales with $O(n)$ regarding the amount of forecast intervals and with to $O(n^2)$ with the number of energy levels, see Section 2.2. The forecasting algorithm is based on Eq. (3), which scales with $O(n)$ regarding the number of involved agents. Eq. (5) looks like it has a linear scaling, too, but is in fact implemented as a recursive series over time, providing $O(1)$ performance in each time step. Overall, a linear runtime scaling is expected with the number of involved agents. To demonstrate this, a performance benchmark is conducted on a personal computer (Intel Core i7-1370, 32 GB of Memory) using a single computation process and the backtesting scenario introduced before. Deviating from that scenario, the total number of storage agents is varied between one and 128 agents. For each number of storage agents, five simulations are conducted to provide a stable measure for the average simulation walltime.

Fig. C.1 shows the average simulation walltime for the simulations depending on the number of storage agents. The offset of approximately 10 s is caused by the other agents in the simulation, which are not changed in this setup. A linear scaling can be observed for a larger number of storage agents.

Data availability

All data and code are available at https://zenodo.org/records/16978510.

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