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Profitability of competing flexibility options in renewable-dominated energy markets: Combining agent-based and machine learning approaches

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ABSTRACT

German transmission system operators received around 400 GW of battery storage connection requests in 2024, an enormous increase from the current 2.3 GW installed capacity. However, uncertainty remains regarding the impact of large-scale storage deployment on electricity market dynamics and a potential cannibalization of profits. To investigate this, we use the open agent-based electricity market model AMIRIS. We extend it with machine learning-based electricity price forecasts during runtime. This enables modelling of competition among flexibility options. We evaluate forecast accuracy and its effects on the operation and profitability of competing flexibility options, with implications for flexibility option revenues. Operational strategies significantly affect revenue: dynamic programming approaches exploiting all profitable spreads yield higher revenue and more charge cycles than threshold-based strategies filtering for spreads exceeding safety margins around mean prices. We then parametrize the model to a 2030 scenario based on the Ariadne report that shows a pathway towards a decarbonized German energy system. At the system level, we identify a profitability plateau for homogeneous storage systems with installed power between 4 to 8 GW and 32 GWh total capacity. Depending on installation costs, annual return on investment can reach around 20% through day-ahead market arbitrage. For heterogeneous storage technologies, requested battery capacities far exceed economically profitable levels implied by simulated market-based returns. This suggests that current German grid connection requests may be economically unsustainable under current market structures. Future research can build on our open tool chain to integrate additional revenue streams, including cross-market participation and system services remuneration.

1. Introduction

The integration of renewable energy (RE) technologies is central to achieving decarbonization targets of the global energy transition. However, it introduces substantial fluctuations in electricity generation, increasing the need for flexibility options (FO) to balance this variability [1]. Among these, battery storage systems (BSS) are particularly promising [2]. In 2024 alone, German transmission system operators received an unprecedented 400 GW and 661 GWh worth of BSS connection requests [3]. By contrast, only 2.3 GW and 3.2 GWh of such storage systems are currently installed. Even if only a fraction of these requests are realized, it clearly signals the growing interest in BSS as essential components of the energy transition. Based on this growing attention, we consider grid-scale BSS as a representative FO, and, unless explicitly stated otherwise, treat FO and BSS interchangeably. This focus on grid-scale BSS does not imply that other flexibility options, such as demand-side management, pumped hydro storage, or sector coupling, are less relevant. Instead, our scope reflects the fact that BSS are currently the dominant subject of large-scale market entry, operate under well-defined market rules in the day-ahead market (DAM), and thus provide a standardized basis for a systematic profitability assessment.

Investment decisions for such BSS require a careful evaluation of both individual-unit performance and system-level implications [4]. As BSS deployment accelerates, understanding how competition among these technologies affects DAM dynamics becomes increasingly

Abbreviations: ABM, Agent-based modeling; BSS, Battery storage systems; DAM, Day-ahead market; E2P, Energy-to-power ratio; FO, Flexibility option; ML, Machine learning; RE, Renewable energy; RTE, Round-trip efficiency; TFT, Temporal fusion transformer; TSO, Transmission system operator.

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important [5]. According to fundamental market mechanics, large-scale storage arbitrage activity influences price formation. Specifically, buying electricity when prices are low increases demand and thus prices, while selling during high-price periods increases supply and reduces prices. Consequently, large-scale BSS capacity will likely have an impact on electricity price formation and may induce cannibalization effects in which BSSs diminish their own revenue potential. This is an important aspect to consider when evaluating the profitability of FOs. Therefore, applied models used to analyze these dynamics must be capable of accurately simulating such interactions.

1.1. Related works

Existing literature covers a broad range of FO assessments focusing on different levels of application ranging from behind-the-meter to front-of-the-meter. While the first group investigates FO applied by individual consumers and businesses [6], the latter are large-scale units operating at utility-scale. Large-scale storage systems can participate in various areas including DAM, intraday markets, ancillary service provision, such as frequency restoration reserve [7], black start capabilities [8], or congestion management [9]. BSS appear to be one of the most promising solutions when compared with eight other FO technologies [10], although profitability remains highly sensitive to operational strategies and system configurations [11]. Technical characteristics such as power rating, energy capacity, and efficiency further determine economic viability [12], yet many such assessments, including analyses of Carnot battery storage [13] and generic price-taking energy storage [14], do not explicitly model competition of decentralized FOs acting with imperfect foresight.

Besides costs, FO investors typically rely on market signals, such as arbitrage potentials, to evaluate FO investments. However, assessments of short-run FO revenues and arbitrage strategies often rely on historical electricity market data [15]. These approaches fail to capture future scenarios which are significantly shaped by the energy transition, including changes in the power plant mix and evolving market dynamics [16]. Price formation is more and more influenced by heterogeneous market actors, particularly the growing share of RE technologies with low marginal costs, conventional peak power plants with reduced operation hours and opportunity costs of cross-sectoral demand [17]. As these price dynamics shift, so does the economic potential of FOs which engage in electricity market arbitrage [18]. This issue is becoming increasingly important as both energy systems and FOs continue to evolve rapidly [19]. Moreover, FO dispatch planning in real-world operation is based on forecasts of future electricity prices rather than perfect foresight. As market dynamics become more volatile and competition among FOs intensifies, the accuracy of these forecasts becomes a critical determinant of profitability.

In parallel, declining market values for RE have been extensively documented. This includes early investigations of long-term intermittent generation value [20], analyses of wind and solar market value factors [21], and more recent work extending these findings to current energy systems [22]. FOs are often assumed to play an essential part in mitigating such cannibalization of RE [23], thus making higher shares of RE in energy systems feasible [24]. However, large-scale deployment of FO may also trigger so-called “avalanche effects” [25], where multiple actors respond simultaneously to similar market signals, thus creating adverse effects. This effect is found in, e.g., heat pump operation [26], electric vehicle charging [27], and household load management [28]. Therefore, assessments of FO have to especially consider both individual actors’ perspective as well as the effects induced to the whole system. Since FO operators typically rely on similar electricity price expectations, their behavior can become synchronized, potentially leading to avalanche effects. This suggests that forecasting quality can influence not only individual dispatch decisions but also amplify system-wide interactions when many actors react simultaneously to similar market signals.

The cannibalization of FOs itself is a relatively new challenge and has not received as much attention in current research [5]. Therefore, the price impacts of FOs should be endogenously captured in the applied models, thus providing more accurate simulation of energy transition scenarios and allowing the consideration of cannibalization effects [29]. Dumitrescu et al. [30] use an equilibrium model to assess long-term profitability of FOs. The authors find that in a French scenario, increased FO penetration reduces revenue potential, but increased uncertainty due to higher RE penetration compensates for this effect. A Greek case study also found reduced FO market values with rising competition which can, depending on the scenario assumptions be compensated by increased fluctuation by RE [31]. In contrast, a study on community electricity storage revealed substantial losses caused by FO cannibalization when competing with sector coupling and demand response [32]. However, this research optimizes community electricity storage settings, not accounting any FO system impacts or application. Reserves markets which are already dominated by FOs no longer yield any significant revenue, and thus do not contribute to FO refinancing [33]. In a case study of the Portuguese energy system, FO competition leads to substitution effects among different FOs, however, the applied optimization model does not provide individual profitability assessments of FOs, but describes a central-planner approach [34]. A case study applying proprietary energy system optimization software investigating a Finnish island also reveals cannibalization among three distinct FO technologies [35].

From a methodological perspective, the competition between FOs can also be addressed using game theoretical models. Such a case study examined homogeneous FO investors and found that rising market competition led to reduced profits [36]. Harder et al. [37] used deep reinforcement learning to simulate FOs in electricity markets. Although they provide an architecture enabling the simulation of competing FOs, their method does not account for price impact by FO actions and the case study provided focuses on a historical time span. Additionally, these approaches are often computationally expensive.

We conclude that a growing body of literature examines FOs across modeling paradigms, from central-planner optimization and equilibrium approaches to agent-based simulations. Cannibalization and substitution effects among FOs have been identified in several contexts, yet many profitability assessments still treat prices as exogenous inputs or rely on historical time spans, which limits insight into future systems with high renewable shares and endogenous short-run market feedback. Our approach complements long-run equilibrium and capacity expansion perspectives by analyzing short-run decentralized competition in the DAM under imperfect, forecast-based decision-making and endogenous price impacts, thereby focusing on realized operational revenues rather than equilibrium outcomes. The three specific gaps this approach addresses, i.e., endogenous market feedback under decentralized competition, the role of technical parameters in determining profitability, and the impact of forecasting quality, are elaborated in the following section.

1.2. Novelty

Our work addresses three specific objectives and consists of three main contributions, as seen in Fig. 1. First, our agent-based model (ABM) of whole-sale electricity markets overcomes the computational limitations of game-theoretical models and avoids the central-planner assumptions inherent to optimization approaches. It thereby enables the simultaneous simulation of a large number of homogeneous and heterogeneous FOs with endogenous market price impacts. Second, by integrating runtime machine learning forecasts into the ABM simulation, the model explicitly captures how individual FO bidding schedules and operation decisions influence market clearing outcomes and, in turn, how changing prices reshape FO profitability. This feedback loop is only partially captured in existing literature and is hard to reproduce with classical optimization models using perfect foresight. Third, by

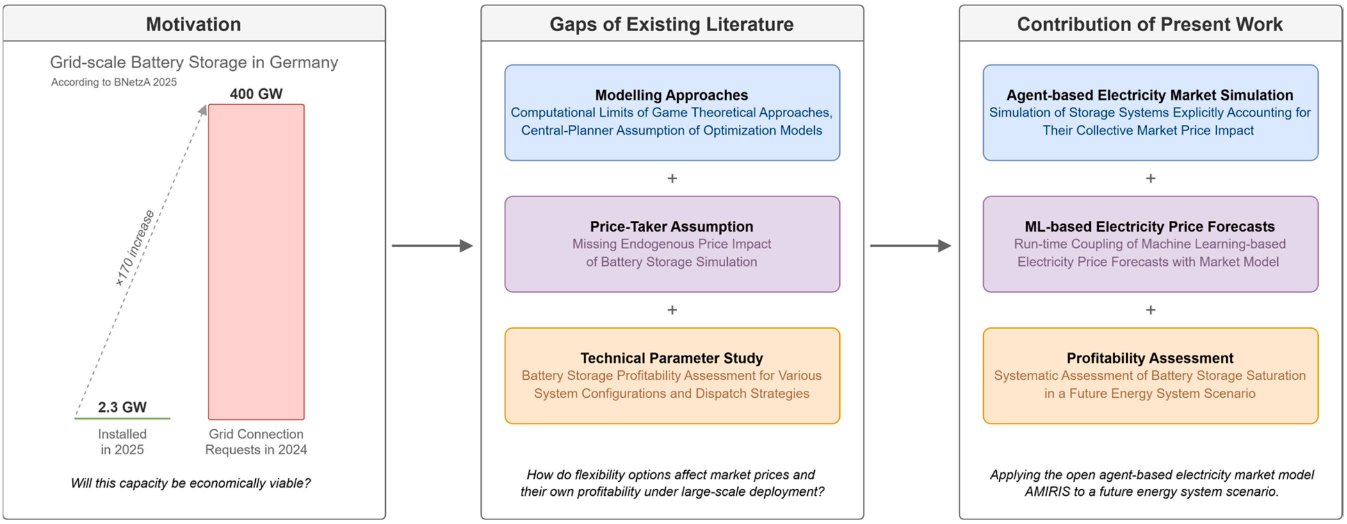

Fig. 1. Schematic representation of motivation for the presented study based on enormous number of grid connection requests in 2024, gaps of existing literature, as well as the main contribution of the present work.

systematically evaluating a wide range of technical parameters, efficiencies, and forecasting paradigms across a comprehensive future energy system scenario, the methodology produces directly applicable insights for storage investment decisions. All components of the modeling toolchain are openly available to ensure full reproducibility.

Therefore, this research seeks to answer the following questions:

1. How are FOs affected by increasing competition on electricity spot markets?
2. Which technical parameters, such as power and energy rating, provide sufficient revenue potential for FOs?
3. What role does the quality of electricity price forecasting play in determining profitability of FOs in competitive markets?

In this paper, we focus exclusively on DAM arbitrage, which represents a prominent and transparent revenue stream for large-scale FOs under current German market design, i.e. uniform pricing in a single-market zone [38]. This scope allows us to isolate competitive dynamics and cannibalization effects. Our findings therefore represent conservative lower-bound estimates of FO profitability, as real-world operators can supplement DAM revenues. The modular architecture of our modeling framework enables future extensions to capture cross-market optimization strategies.

We do not claim novelty in endogenizing cannibalization effects per se. Long-run equilibrium and energy system optimization models inherently capture such effects through market clearing and zero-profit conditions. Our contribution differs in focus and methodology. By coupling an electricity market simulation with runtime electricity price forecasts, we assess realized revenues, cycling behavior, and saturation effects that arise from decentralized dispatch decisions. This allows us to analyze short-run operational competition among flexibility options under imperfect foresight and decentralized decision-making.

This paper is structured as follows. In Section 2, we present our material and methods, including the applied ABM. In Section 3, we describe the findings derived from our electricity market simulations. In Section 4, we discuss the results and identify important limitations. In Section 5, we give a summary of the findings and provide an outlook on potential future research avenues.

2. Material and methods

Our analysis is based on a fully automated, open modeling toolchain (see Fig. 2) to ensure transparency and reproducibility. At its core, the open electricity market model AMIRIS [39] is used to simulate the DAM over one year with hourly resolution (see Section 2.1). To endogenously model competing FOs, we apply electricity price forecasts generated by a dedicated machine learning (ML) algorithm. This algorithm is trained on a wide range of synthetic scenario data [40] created with AMIRIS-Scengen [41]. The forecasting algorithm is integrated into a co-simulation with AMIRIS, where a forecasting agent distributes the externally generated price forecasts to its clients, the FO agents. AMIRIS is then parameterized based on a well-documented and established scenario [42] (see Section 2.2). Finally, we systematically vary the technical parameters of FOs to assess their profitability and analyze market dynamics. In the following subsections, we describe the relevant components of the toolchain.

2.1. Electricity market modelling using AMIRIS

AMIRIS, the *A*gent-based *M*arket model for the *I*nvestigation of *R*enewable and *I*ntegrated energy *S*ystems [39], is an open-source[1] model developed since 2008 and released publicly in 2021 [43]. Built on the flexible framework FAME [44,45], AMIRIS simulates the DAM based on individual agent interactions [12] while considering different policy frameworks [46] and cross-border market coupling effects [47]. The model comprises five main agent types. These consist of power plant operators, traders, market operators, regulators and FOs. Fig. 13 in the Appendix illustrates these agents and their interactions through flows of information, energy, and money. Each agent type operates based on individual rationality and information sets, employing rule-based strategies, heuristics, optimization methods, or ML algorithms. Market outcomes like price dynamics thus emerge from the interaction of these agents [48].

The DAM operates as a uniform-price auction where agents submit hourly supply and demand bids. Conventional and renewable power plant operators submit supply bids based on their marginal generation costs including optional mark-ups and mark-downs. FO operators submit both supply bids (when discharging) and demand bids (when charging), with bid prices determined by their operational strategy, see also Section 2.1.1. Demand traders formulate their bids in order to meet their load profiles. The DAM operator aggregates all bids into supply and demand curves and determines the market-clearing price where supply meets demand for each hour. All accepted bids receive (for supply) or

[1] gitlab.com/dlr-ve/esy/amiris (accessed on 26th April 2026)

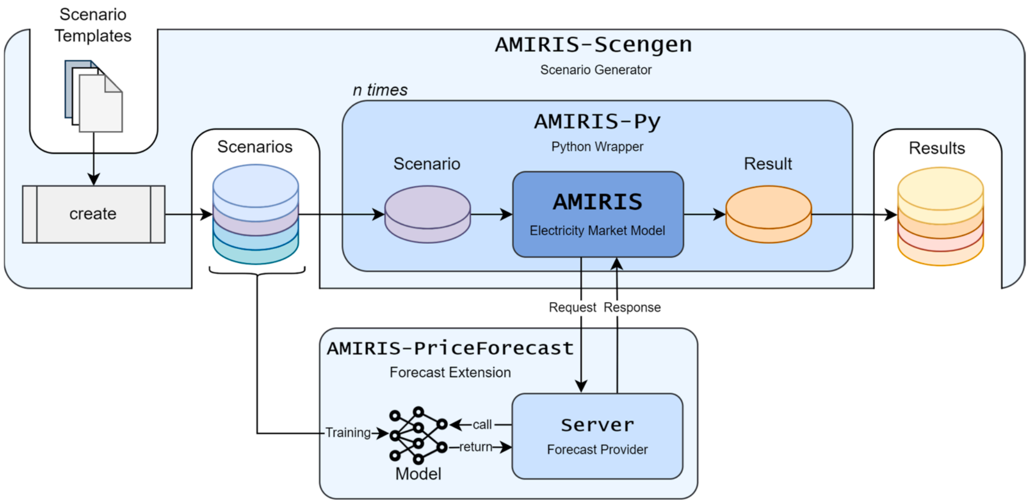

Fig. 2. Modelling setup of the open toolchain used in this study. At its core, the agent-based electricity market model AMIRIS simulates the day-ahead market; the AMIRIS-PriceForecast module provides machine learning-based electricity price forecasts during runtime; and AMIRIS-Scengen generates the synthetic scenario data used for model training. Arrows indicate data and information flows between components.

pay (for demand) this uniform clearing price.

Similar to other energy system models, users define and provide relevant input data [49]. In the context of AMIRIS this translates to power plant park structure, RE generation timeseries, demand data, and operational cost data. For FO operators, additional parameters include storage capacity (MWh), charging and discharging power limits (MW), round-trip efficiency, and strategy-specific parameters. Primary outputs of AMIRIS cover hourly DAM electricity prices, market-based dispatch schedules for all generation and FOs, and financial metrics, such as costs and revenues, for all market participants. AMIRIS has been back-tested for the German [50] and Austrian [51] DAM, demonstrating good agreement between simulated and historical electricity prices.

The current AMIRIS implementation focuses exclusively on DAM operations. Additional revenue streams for FOs, such as intraday markets, balancing reserves, or ancillary services, are not modeled. This limitation means our revenue estimates represent lower bounds, as real-world storage operators typically participate across multiple markets simultaneously [52].

2.1.1. *Modelling flexibility options*

FOs can choose between an opportunistic strategy that exploits all profitable spreads via dynamic programming [13] or a conservative strategy that trades only when spreads exceed safety margins around mean prices when performing arbitrage at the DAM [53].

As Eq. (1) shows, the opportunistic strategy aims to maximize total revenue R by exploiting all profitable price spreads on the DAM over the planning horizon T in time steps t of duration 1 hour each. Based on the forecasted electricity price p in EUR/MWh, the FO chooses to either charge c or discharge d a certain amount of energy in MWh. A dynamic programming algorithm evaluates possible decision sequences to identify the optimal state of charge SOC in MWh for each time step, see Eq. (2) while considering discharging efficiency η_d and charging efficiency η_c and accounting for technical constraints. These include capacity limits as shown in Eq. (3), charging energy and discharging energy limits as shown in Eq. (4), and mutual exclusivity of charging and discharging operations as shown in Eq. (5). Thereby, the dynamic programming approach identifies an optimal dispatch sequence conditional on the given price forecast and technical constraints, rather than a system-optimal or equilibrium outcome.

$$\mathit{maximize}\ R = \sum_{t=1}^{T} p_t \times (d_t - c_t) \tag{1}$$

$$SOC_t = SOC_{t-1} - \frac{1}{\eta_\mathrm{d}} \times d_t \ + \eta_\mathrm{c} \times c_t \tag{2}$$

$$SOC_{\min} \leq SOC_t \leq SOC_{\max} \tag{3}$$

$$0 \leq c_t \leq c_{\max};\ \ 0 \leq d_t \leq d_{\max} \tag{4}$$

$$c_t \times d_t = 0 \tag{5}$$

The conservative strategy employs a heuristic approach that filters charging and discharging opportunities based on whether price spreads exceed predefined safety margins around the mean forecasted price. This strategy trades only when prices deviate sufficiently from the expected price average. For instance, the FO would aim at charging if the expected price p is below the mean price μ lowered by a safety margin δ, see also Eq. (6). The discharging routine works in a similar manner, but here the safety margin δ is added to the mean price, see also Eq. (7).

$$c_t = h(t)\ c_{max}\ \mathit{if}\ p_t < \mu - \delta,\ \mathit{else}\ c_t = 0 \tag{6}$$

$$d_t = h(t)\ d_{max}\ \mathit{if}\ p_t > \mu + \delta,\ \mathit{else}\ d_t = 0 \tag{7}$$

$$\delta = \mu \times \frac{1 - \eta_\mathrm{c} \times \eta_\mathrm{d}}{1 + \ \eta_\mathrm{c} \times \eta_\mathrm{d}} \tag{8}$$

The safety margin δ, see Eq. (8), is chosen to compensate the imperfect (dis-)charging efficiencies and ensures that the system only participates in arbitrage when price deviations are sufficiently large. Mean price and safety margin are recalculated for each planning horizon T to provide a dynamic reference point that adapts to changing market conditions. The amount of charged or discharged energy in Eqs. (6) and (7) is determined by a heuristic h that allocates (dis-)charged energy more strongly towards hours with larger deviations from the price mean. The technical constraints introduced in Eqs. (2) to (5) are also applied.

2.1.2. *Electricity price forecasting during runtime*

Both FO strategies require electricity price forecasts p to optimize bidding schedules. Price forecasts typically cover at least the next 24 hours. Previous AMIRIS versions used simplified "naïve" forecasts suitable only for single-FO scenarios [54]. To enable realistic endogenous multi-FO competition (addressing objective 1 and 3), we integrated ML-based electricity price forecasting, which has demonstrated robust performance even in highly renewable future scenarios [40].

We developed AMIRIS-PriceForecast [55], a dedicated ML-based forecasting module that operates in co-simulation with AMIRIS to provide electricity price predictions during model runtime. This module can employ different ML algorithms, such as Temporal Fusion Transformers (TFT) [56], trained on synthetic market data, including renewable generation patterns and demand profiles, to generate hourly price forecasts. For the first time in AMIRIS, this approach captures complex, non-linear relationships between market fundamentals and price outcomes, such as FO behavior, that simpler heuristics cannot represent.

Fig. 3 illustrates the forecasting workflow. FO agents request price forecasts from a centralized forecasting agent (PriceForecasterApi), which delivers identical forecasts to all competing agents. The use of a uniform forecast for all agents is a deliberate modelling choice. It establishes a well-controlled baseline in which performance differences between competing storage units arise exclusively from technical parameters rather than informational heterogeneity. Furthermore, it represents a conservative assumption with respect to cannibalization: if agents used heterogeneous forecasting models, some would outperform others, reducing the synchronization of charging and discharging behavior that amplifies collective market price impacts. However, the presented algorithm could be enhanced to also provide agent-specific forecast errors.

To improve computational efficiency, PriceForecasterApi maintains a cache of recent forecasts and only calls the external AMIRIS-PriceForecast module when cached forecasts fail to meet predefined accuracy thresholds or when forecasts for new time periods are needed. Upon receiving a request, AMIRIS-PriceForecast loads its pre-trained model and generates time series predictions tailored to the specific forecast horizon requested. The coupling between AMIRIS (Java-based) and AMIRIS-PriceForecast (Python-based) is implemented through a standardized REST API interface using FastAPI,[2] enabling efficient communication. This modular architecture allows researchers to extend or replace forecasting algorithms independently of the main AMIRIS codebase, ensuring the framework can incorporate advances in time series forecasting methods as they emerge.

2.2. Energy transition scenario

Our study focuses on the German DAM zone. The data is based on the "Ariadne" scenario report [42], which is widely recognized for its comprehensive analysis of potential pathways for the German energy transition toward climate neutrality by 2045 (see Fig. 4). The Ariadne project,[3] funded by the German Federal Ministry of Research, Technology and Space, employs multiple integrated modeling approaches to assess the feasibility, costs, and sectoral implications of different transformation pathways, making it a particularly robust foundation for energy system analysis. The economic and demographic assumptions underlying the Ariadne scenario report are based on the so-called "Middle of the Road" scenario among the Shared Socioeconomic Pathways as defined in [57]. The scenarios contain detailed assumptions about RE expansion, sector coupling mechanisms, hydrogen deployment strategies, and the systematic phase-out of fossil fuels across all economic sectors. Specifically, we utilize the "mix" subscenario, which assumes the use of a mixed energy carrier portfolio based on electricity, hydrogen, and synthetic green fuels in final energy consumption. This subscenario reflects a diversified approach to decarbonization where different sectors employ the most suitable clean energy carriers based on technical and economic considerations.

Table 1 summarizes the key generation capacities, demand projections, and CO_2 certificate costs from the Ariadne 2030 "mix" scenario that form the baseline for our analysis. All values are taken directly from the Ariadne report without modification. We selected the year 2030 as our temporal focus, as many of the storage connection requests [3] under consideration aim to be realized within this timeframe. Flexibilization of demand is already inherently integrated in the load profiles, reflecting the scenario's consideration of demand-side management and behavioral adaptations. However, since the Ariadne scenarios predate the recent storage connection requests, they do not account for potential market impacts of large-scale storage deployment. Therefore, we extend this baseline by introducing additional competing FOs. We systematically vary storage capacity and power, operational strategies (opportunistic vs. conservative), and forecasting quality (perfect foresight vs. ML-based) to isolate storage competition effects from the broader energy transition dynamics captured in the Ariadne scenario.

Given the inherent uncertainty in projecting battery storage costs to 2030 and to ensure our profitability assessment remains robust across plausible future scenarios, we employ a sensitivity analysis approach rather than assuming fixed cost values. Storage investment costs comprise two components: converter costs ranging from 50 EUR/kW to 200 EUR/kW [58] and storage costs ranging from 100 EUR/kWh to 400 EUR/kWh [59]. These ranges reflect current market conditions and projected cost reductions based on learning curves and economies of scale expected over the coming years. All storage systems are assumed to have a round-trip efficiency (RTE) of 80 %. This acts as a lower limit for the homogeneous expansion analysis in Section 3.2.1, while the heterogeneous analysis in Section 3.2.2 explores a broader range up to 90 % RTE.

It should be noted that the Ariadne scenario represents one plausible decarbonization pathway among several. Variations in RE expansion rates, fuel prices, or demand-side developments would affect the simulated price dynamics and thus the absolute revenue levels reported. The relative findings, such as competitive technical specifications, should therefore be interpreted as scenario-specific results, and their transferability to substantially different energy system scenarios require further investigation.

3. Results

The results are organized in two main sections. Section 3.1 presents the methodological advancements developed to close research objective 3, demonstrating the performance of our enhanced analytical framework. Section 3.2 examines the profitability of FOs in the future energy system scenario, providing insights concerning research objectives 1 and 2.

3.1. Methodological advances

Addressing research objective 3, the role of forecasting quality in determining flexibility option profitability, we first evaluate the methodological improvements to AMIRIS, building on [40] which demonstrates that ML algorithms are applicable for electricity price forecasting even in scenarios with high shares of renewable energies. For this, we assess the accuracy of electricity price forecasts generated by the AMIRIS extension AMIRIS-PriceForecast. Our approach employs a TFT algorithm for electricity price prediction, which proved to be highly accurate for this application [40]. The forecasting model integrated into AMIRIS-PriceForecast is iteratively called during AMIRIS runtime, generating DAM electricity price forecasts p_t to p_{t+23} based on previous electricity prices p_{t-24} to p_{t-1} and historical residual load L^{R}_{t-24} to L^{R}_{t-1} and forecasted residual load L^{R}_{t} to L^{R}_{t+23}.

Fig. 5 illustrates cumulative storage revenues achieved using different TFT hyperparameter settings, revealing the direct impact of different forecasting methods on FO performance. Each curve represents a single deterministic simulation run. All market inputs are identical across configurations; multiple runs therefore yield identical results besides some minor numerical differences from the ML prediction. We show two benchmarks: a perfect foresight, representing the theoretical maximum revenue potential calculated ex-post on the realized market

[2] github.com/fastapi/fastapi (accessed on 26th April 2026)

[3] ariadneprojekt.de (accessed on 26th April 2026)

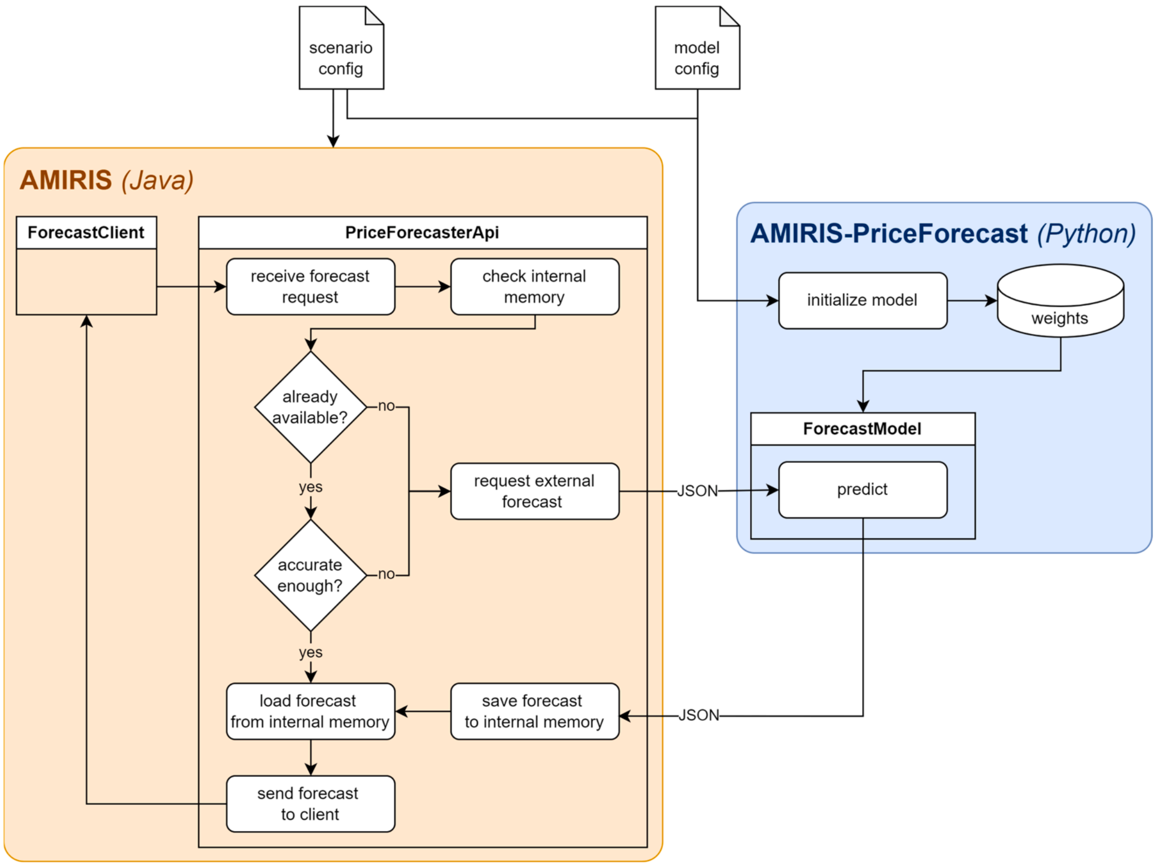

Fig. 3. Workflow of the runtime electricity price forecasting coupling between AMIRIS and the AMIRIS-PriceForecast module. Flexibility option agents request price forecasts from the centralized PriceForecasterApi, which serves cached forecasts where available or queries the external Python-based forecasting module via a REST API interface. For instance, the forecasting module generates 24-hour ahead price predictions based on previous electricity prices and residual load of the AMIRIS simulation.

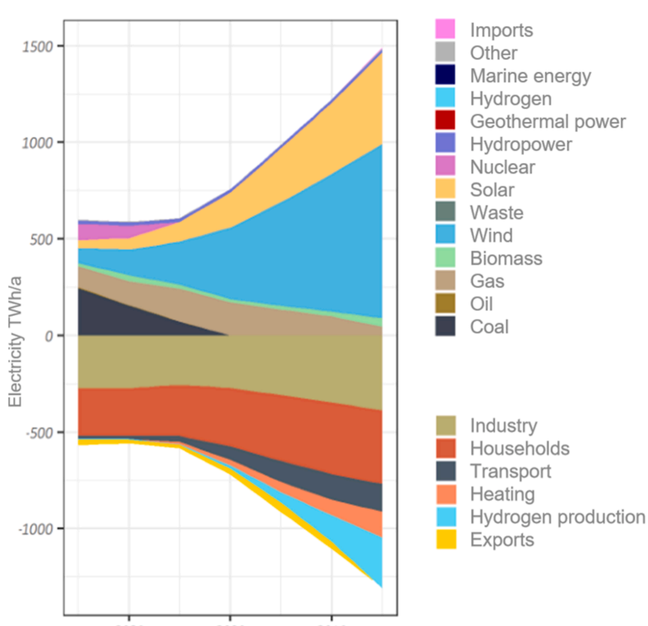

Fig. 4. Electricity generation and consumption for Germany in the Ariadne 2030 'mix' scenario used as the baseline for this study, showing the projected capacity mix and annual load under a diversified decarbonization pathway; adapted with permission from [42].

Table 1
Energy system parameters derived from [42] which define the key parameters for the energy transition scenario. Installed capacities are given in GW, annual electricity load in TWh/a, and CO_2 certificate costs in EUR/t. Hard coal, lignite, and nuclear capacity are fully phased out by 2030 in this scenario.

Parameter		Value	Unit
Capacities	Photovoltaics	218.4	GW
	Wind onshore	127.2	
	Natural gas	30	
	Wind offshore	25	
	Biomass	15.7	
	Hydrogen	15.3	
	Run-of-river	12.6	
	Other non-renewable	0.9	
	Hard coal	0	
	Lignite	0	
	Nuclear	0	
CO_2 certificate costs		200.0	EUR/t
Electricity demand		615.8	TWh/a
Greenhouse gas reduction compared to 1990		65	%

clearing prices under price-taking assumptions, and a “naïve” time shift method using the previous 24 hours as a forecast [60]. The latter causes the storage to capture less than 40 % of the maximum potential revenues. Our analysis of various hyperparameter configurations demonstrates that model architecture significantly influences revenue outcomes. The best-performing ML prediction incorporates future covariates, achieving nearly 80 % of potential revenues. This finding aligns with recent research showing substantial error reduction when integrating future covariates in time series forecasting [61]. While this

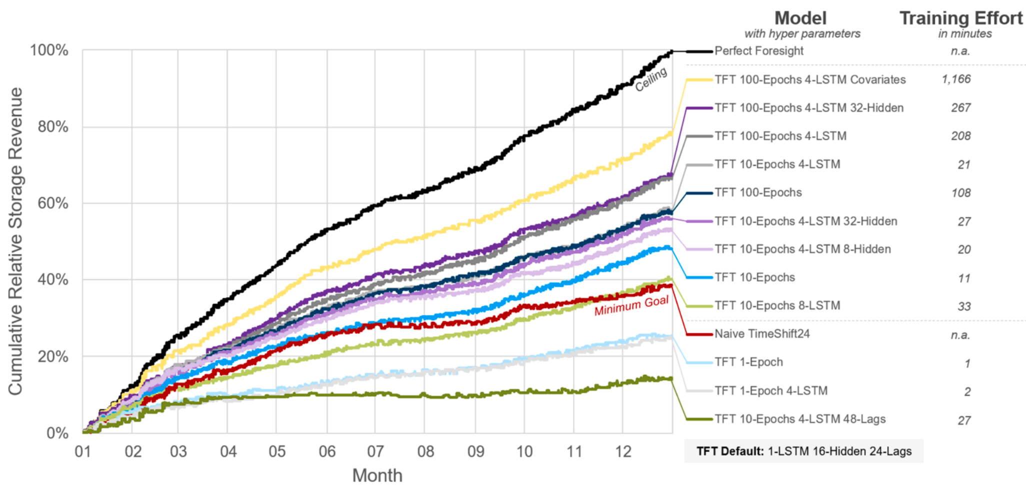

Fig. 5. Impact of Temporal Fusion Transformer hyperparameter configurations on required training effort in minutes and on cumulative day-ahead market revenue of a 1 MW and 5 MWh battery storage system over one simulation year. The perfect foresight[a] upper bound (black) and a simple naïve 24-hour time-shift (red) are shown for reference. Forecast accuracy metrics (MAE, RMSE) for electricity price forecasts in the energy market domain using the TFT architecture are reported in [40].
[a]The perfect foresight benchmark represents a theoretical maximum revenue potential calculated ex-post on the realized market clearing prices under price-taking assumptions.

enhanced performance requires significantly higher computational training[4] costs, four to five times greater than alternative models, the training effort can be considered uncritical since the trained model is applicable to a wide range of simulation scenarios [40]. Each prediction call accounts for approximately 0.1 s including negligible overhead by the model coupling via FastAPI.

To examine how forecasting quality affects FO operation, we analyze a 1 MW, 5 MWh price-taking BSS with a RTE of 80 % under two forecasting modes: perfect foresight, representing ex-post optimal operation, and model-endogenous ML price forecasts. Each forecasting mode is combined with two operational strategies: opportunistic, which exploits all expected price spreads, and conservative, which acts only on significant expected spreads.

Fig. 6 illustrates operational differences during a representative week across four scenarios revealing the impact on full load cycles and revenue. With perfect foresight, the opportunistic strategy (Fig. 6a) captures all profitable arbitrage opportunities, while the conservative strategy (Fig. 6b) filters out smaller spreads, missing some profitable trades (compare 6aI/6bI, or 6aII/6bII). ML-based forecasting introduces prediction errors that cause suboptimal dispatch. Under the opportunistic strategy (Fig. 6c), forecast errors trigger unprofitable charging and discharging events that perfect foresight would avoid (compare 6aI/6cI). Under the conservative strategy (Fig. 6d), forecast errors cause extended idle periods as predicted prices do not exceed safety margins, missing actual arbitrage opportunities (compare 6bI/6dI). Regardless of forecast quality, the conservative strategy consistently exhibits less activity than the opportunistic approach (compare 6cII/6dII).

While Fig. 6 provides a detailed view of a single week, Fig. 7 reveals systematic patterns across all combinations by presenting an annual perspective in hourly resolution. Storage charging (blue areas) occurs primarily during nighttime and midday low-price periods, while discharging (red areas) results from peak prices during morning and evening. ML forecasting errors create noticeably noisier activity patterns, which are particularly evident in the opportunistic strategy (Fig. 7b). The revenue analysis demonstrates substantial impacts from both strategy choice and forecasting accuracy. Using perfect foresight as the baseline (opportunistic strategy, Fig. 7a), the conservative strategy achieves approximately 79 % of maximum revenues (Fig. 7b). ML based forecasting reduces performance to 73 % for opportunistic (Fig. 7c) and 62 % for conservative strategies (Fig. 7d). Cycling behavior also varies significantly across scenarios. Perfect foresight with opportunistic strategy results in 359.4 full charge cycles[5] over the simulation year (nearly one per day). In contrast, the conservative approach reduces this number to 227.5 cycles. The opportunistic strategy joined with ML forecasting produces 381.1 cycles (indicating increased cycling due to forecast errors). This increased number of cycles could further impact profitability if cycling costs were considered. 207.2 cycles result when the conservative strategy is combined with ML forecasts, strengthening the earlier finding that forecast errors can lead to missed opportunities depending on the operational strategy employed.

3.2. Profitability of flexibility options

This section aims to define technical parameters, such as energy and power rating, for FOs, thus addressing research objective 2, and then examining how competitive dynamics affect profitability, which addresses research objective 1. To compare the profitability of differently scaled FOs, particularly BSS, we compute the return on investment (ROI), similar to the definition in [62]. ROI, see Eq. (9), is calculated as the ratio of net cashflow CF_t for year t from earnings e_t minus costs c_t from (dis-)charging, see Eq. (11), to the total installation costs $Cost_0$, see Eq. (12). The installation costs include the power-based converter costs $c_{converter}$ and the energy-based storage cost $c_{storage}$. The result is expressed as a percentage where high values express superior profitability. This metric provides a quick payback-oriented perspective for initial investment screening.

ROI focuses on installation costs and market revenues only, as they represent the dominant leverages for investment viability across the parameter space examined. Although the analyzed storage configurations differ in both power and energy capacity, total installation costs are primarily driven by capacity-related components. In contrast, operating and maintenance costs, which are approximately 2.5 % of converter capital costs per year for utility-scale battery storage [58], are

[4] Model training was performed on a system equipped with an Intel® Core™ i7-11850H processor (2.50 GHz) and 32 GB of RAM.

[5] One full charge cycle indicates a complete charge and discharge of the storage, whether it occurs all at once or is accumulated over multiple partial cycles.

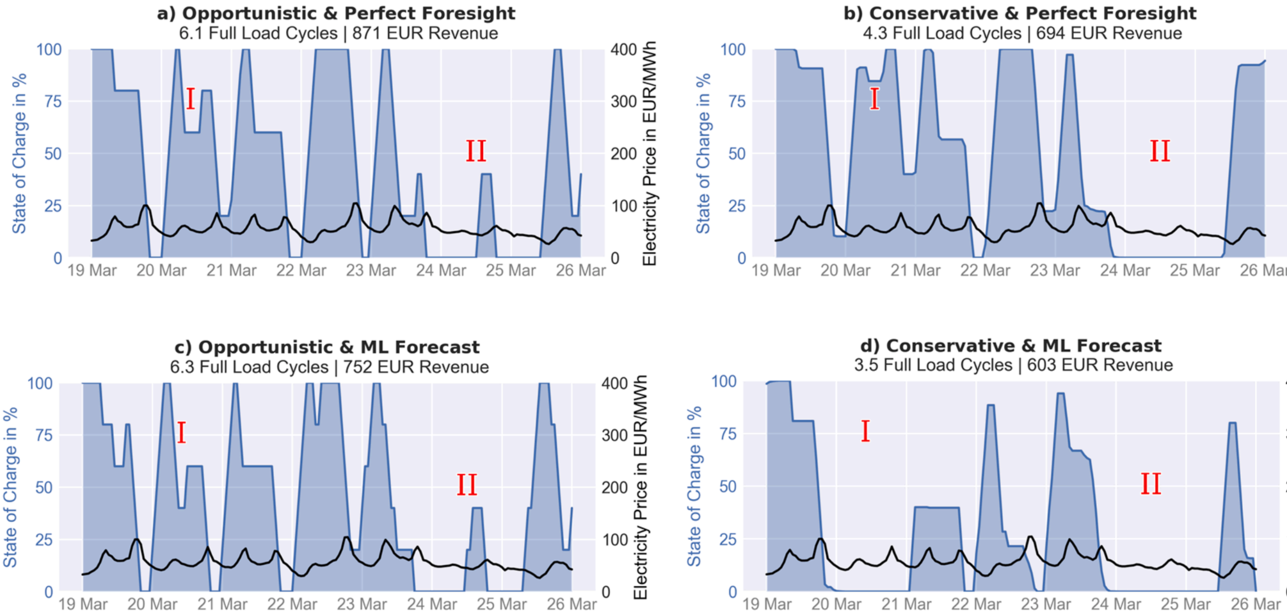

Fig. 6. State of charge (blue area, MWh) and day-ahead electricity price (black line, EUR/MWh) during a representative simulation week for a 1 MW and 5 MWh battery storage system under four combinations of operational strategy (opportunistic vs. conservative) and forecast type (perfect foresight vs. machine learning).

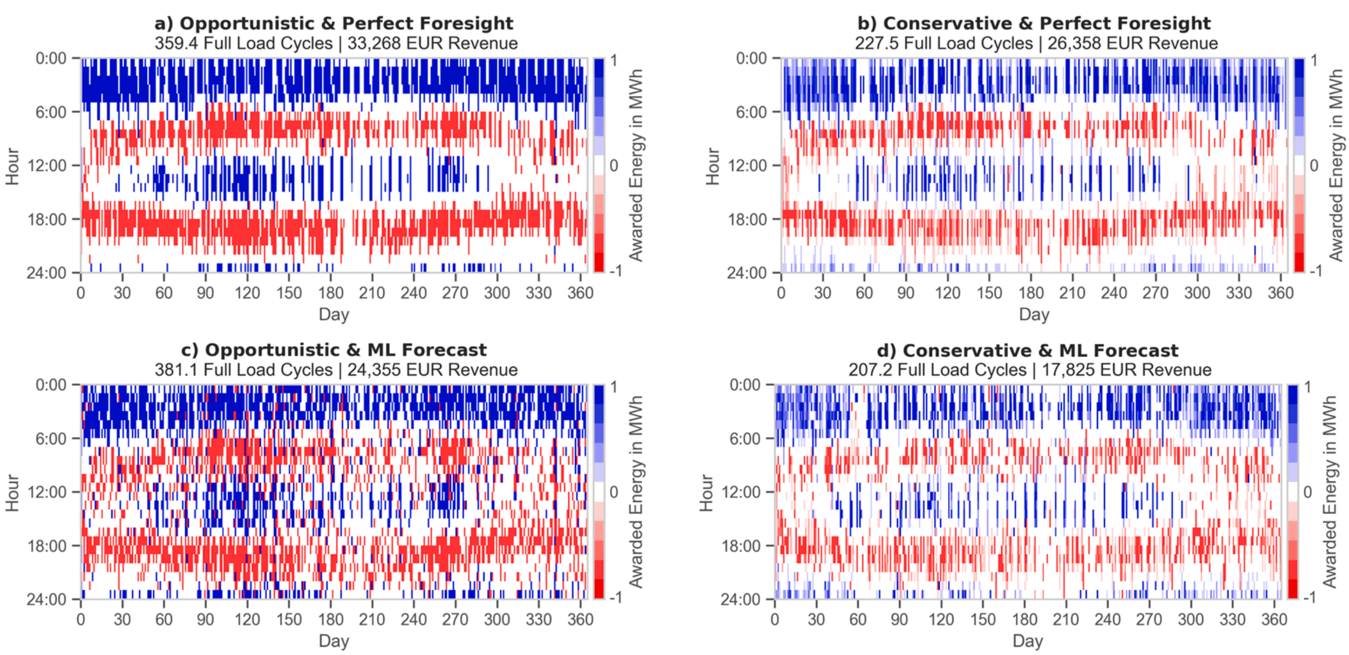

Fig. 7. Storage activity over a full simulation year in hourly resolution for a 1 MW and 5 MWh battery storage system under four combinations of operational strategy (opportunistic vs. conservative) and forecast type (perfect foresight vs. machine learning). Blue areas indicate charging; red areas indicate discharging.

power-based and therefore account for a comparatively small and largely uniform cost contribution across configurations. As a result, their inclusion would shift all ROI values downward by a similar margin without affecting the relative ranking of technical specifications. Cycle-induced degradation costs, however, are configuration-dependent and would partially offset the revenue advantage of the opportunistic strategy relative to the conservative strategy, as discussed further in Section 4. Accordingly, the reported ROI values should be interpreted as upper bounds, subject to site-specific operating and maintenance costs and cycle-induced degradation costs that vary with the chosen operational strategy.

Further, as ROI does not cover annualized capital costs, we solve Eq. (10) for the Internal Rate of Return (IRR), as also used in [63] assuming an estimated operational lifetime and constant cashflow to provide an additional financial performance metric.

$$ROI = \frac{CF_{t=1}}{Cost_0} \times 100 \tag{9}$$

$$NPV = CF_{t=1} \times \sum_{t=1}^{n} \frac{1}{(1+IRR)^t} - Cost_0 = 0 \tag{10}$$

$$CF_t = e_t - c_t \tag{11}$$

$$Cost_0 = power \times c_{converter} + capacity \times c_{storage} \tag{12}$$

3.2.1. Homogeneous flexibility options expansion

Fig. 8 presents ROI for homogeneous large-scale BSS in the 2030 scenario with fixed power at 8 GW and varying storage capacity (8 GWh to 64 GWh) under different cost assumptions. Fig. 9 shows ROI when the capacity is fixed at 32 GWh and the storage power varies from 1 GW to 12 GW. In all cases, converter costs range from 50 EUR/kW to 200 EUR/kW [58] while the storage costs range from 100 EUR/kWh to 400 EUR/kWh [59], and RTE is at 80 %. We visualize these results as contour plots of isoROI lines in dependence of converter costs and storage costs as this representation offers several analytical advantages. It reveals the trade-off relationship between power and energy cost components, enables identification of cost thresholds for investment viability (e.g., minimum 10 % ROI), and facilitates comparison across different technical configurations. The analysis reveals that annual ROI can exceed 18 % under favorable cost conditions, with highest numbers at 32 GWh total capacity and 4 to 8 GW installed power.

When interpreting these results, it is crucial to consider the different specifications of FO in terms of their energy-to-power (E2P) ratio. Systems with low E2P ratios are generally designed for short-duration operation. These systems can discharge power for only a short period, e.g., 1 hour in the case of 8 GW/8 GWh, but charging also takes just 1 hour. In contrast, systems with high E2P ratios can discharge power over a much longer period, making them more suitable for long-duration storage. Our results show that both systems with low E2P ratios, such as 8 GW/8 GWh, and systems with very high E2P ratios, such as 1 GW/32 GWh, exhibit significantly lower ROI. This highlights the importance of tailoring technical specifications to the specific needs of the energy system. The findings can be better understood by investigating the resulting electricity price dynamics. Fig. 15 in the Appendix provides a comprehensive scan of different storage systems and their resulting activity and price impact. We note that systems with low E2P ratios can charge and discharge rapidly, but cannot benefit from longer-duration price changes whereas systems with larger E2P generally profit from these periods. In these cases, however, storage costs represent the major share of total installation cost, thus causing maximum profitability at an intermediate E2P configurations. In contrast, specific system combinations, i.e., high-capacity and/or high-power systems, impact market prices by elevating low prices during charging and suppressing high prices during discharging, thereby cannibalizing their collective revenue potential.

A crucial distinction of our methodology is the endogenous modelling of electricity market prices, explicitly capturing how individual FO behavior influences market dynamics. This contrasts with studies such as [15], that treat prices as exogenous inputs, enabling us to identify saturation points where collective FO impacts reduce overall profitability. These saturation points describe realized operational profitability under the assumed market design and short-run competition, and should not be interpreted as long-run equilibrium capacity outcomes. The impact of the ML training volume on ROI calculation is described in Fig. 14 in the Appendix.[6]

To complement our profitability analysis based on ROI, we calculate the IRR for one of the best performing technical configuration, 6 GW/32 GWh. The IRR accounts for the time value of money and financing considerations that the ROI does not capture, providing an additional metric for such a long-term investment. We examine IRR across operational lifetimes ranging from 10 to 20 years, applying the same cost assumptions used in the ROI analysis (converter costs: 50 – 200 EUR/kW; storage costs: 100 – 400 EUR/kWh). Fig. 10 presents the resulting IRR values, where positive results indicate profitable investments assuming constant annual cash flows from DAM arbitrage throughout the operational period. In general, longer operational lifetimes and lower capital costs yield higher IRR values. Under moderate cost assumptions, BSS require minimum operational periods of 10 years to achieve profitability, with IRR values reaching approximately 20 % for systems operating over 20-year lifetimes and with optimistic cost assumptions. The IRR analysis reinforces that the 6 GW/32 GWh configuration represents a robust investment opportunity as long as cost assumptions are favorable.

3.2.2. Heterogeneous flexibility options expansion

To provide more granular insights for the impact of BSS technical parameters on profits, we conduct detailed analysis varying E2P ratios and RTE. Maintaining fixed installed capacity at 6 GWh, we examine temporal characteristics ranging from short-term storage, E2P ratio of 1, to more medium-term storage, E2P ratio of 8, with RTE values spanning from 60 % to 95 % to represent different storage technologies. They all operate under the opportunistic strategy with ML based price forecasts. Fig. 11 illustrates annual storage revenue excluding investment costs. The E2P ratio emerges as the dominant factor in revenue maximization, with best performance occurring between ratios of 3.5 – 7.5 for the analyzed energy scenario. This reflects electricity price dynamics in the Ariadne scenario, where high RE shares lead to extended periods of very low prices when demand is fully met by renewable generation, followed by periods requiring expensive conventional peak generation. FOs with intermediate E2P ratios most effectively exploit these price spreads. Higher RTEs consistently improve revenue potential. It is worth noting that RTE can also be interpreted as operational cost where low efficiency translates to high cycling costs. Surprisingly, short-term storage systems with E2P ratios below 1.5 generate losses rather than profits. Since capacity is fixed at 6 GWh, low E2P ratios correspond to high-powered systems which significantly impact electricity prices, undermining performance under opportunistic strategies. This is in contrast to studies using historical price data [15] and frequency restoration reserves markets [12], which identify high-power storage as the most profitable configuration. Importantly, our results do not suggest high-powered FOs cannot be profitable in the studied scenario, but rather that they require enhanced operational strategies accounting for their market price influence. This sensitivity analysis also reveals that revenue per installed MWh, as well as ROI follows the same structure to the shown total revenue, while revenue per installed MW increases with higher E2P ratios.

We then select three distinct configurations from the analysis, each yielding roughly equivalent total revenues but representing different technical niches to be analyzed in direct competition with each other:

- T1: E2P of 3, RTE of 90 %, a short-term optimized FO, e.g., a BSS
- T2: E2P of 7, RTE of 80 %, designed for medium-term applications, e.g., a pumped-hydro storage
- T3: E2P of 5, RTE of 70 %, a lower efficiency storage system, e.g., a heat/air storage

We investigate economic performance for these three technologies operating individually and in competitive scenarios. Fig. 12 shows annual total revenue, as well as revenue per installed MW and revenue per installed MWh, for the three individual and two competition cases. In the competition case with 2 GWh each, the total revenue across all storages remains similar to the individual cases. T1 accounts for 37 % of total revenue, while T2 and T3 achieve 32 % and 31 % respectively. This suggests that, in a competitive case, T1 can increase its revenue share by exploiting its short-term flexibility niche, which remains unaffected by the more medium-term orientated T2 and T3. When total capacity triples to 6 GWh, market dynamics shift substantially affecting all

[6] Figure 14 in the Appendix shows the effect of training length on ROI for BSS. When increasing training epochs from 1 to 50, we observe that the applied Temporal Fusion Transformer does not significantly improve if trained for more than 10 epochs. Compared to the analysis in Figure 5, we have increased the training data available to the model by a factor of five, thus resulting in 30 training scenarios with 8760 time steps each. Together with the used hyperparameter settings (100 epochs, 4 LSTM layers, 32 hidden layers, 24 hours lookback) this allows the model to converge quickly.

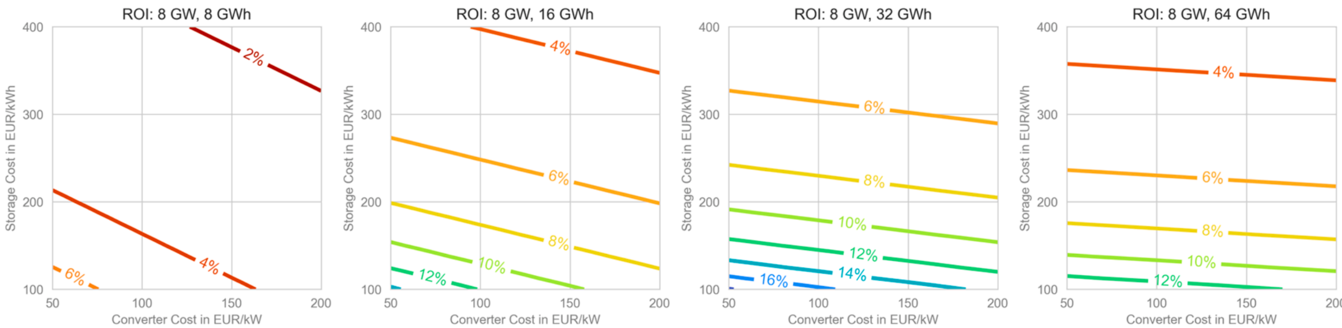

Fig. 8. Annual return on investment (ROI, %) for homogeneous battery storage systems with fixed installed power of 8 GW and storage capacity varying from 8 GWh to 64 GWh, shown as isoROI contour lines across the full range of converter costs (50 – 200 EUR/kW) and storage costs (100 – 400 EUR/kWh). Round-trip efficiency is fixed at 80 %. Results are based on the 2030 Ariadne scenario with opportunistic strategy and machine learning forecasts.

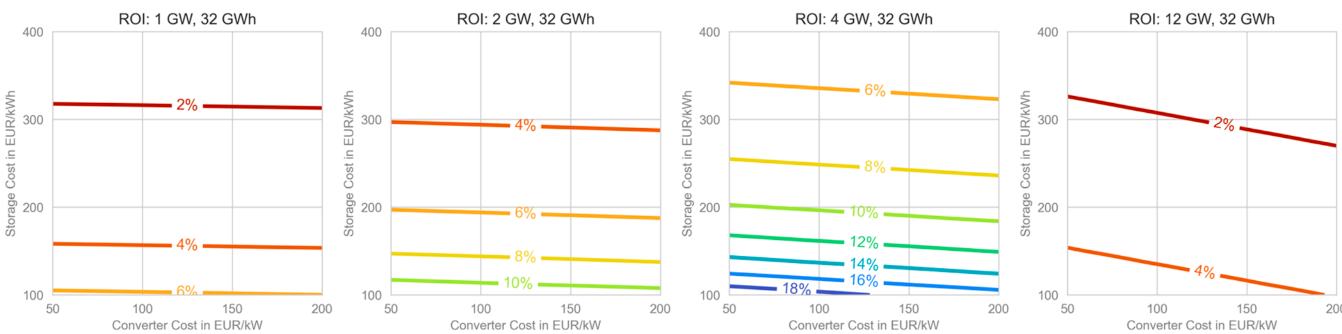

Fig. 9. Annual return on investment (ROI, %) for homogeneous battery storage systems with fixed storage capacity of 32 GWh and installed power varying from 1 GW to 12 GW, shown as isoROI contour lines across the full range of converter costs (50 – 200 EUR/kW) and storage costs (100 – 400 EUR/kWh). Round-trip efficiency is fixed at 80 %. Results are based on the 2030 Ariadne scenario with opportunistic strategy and machine learning forecasts.

Fig. 10. Internal rate of return (IRR) for the 6 GW and 32 GWh battery storage configuration under operational lifetimes of 10 to 20 years, across the full range of converter costs (50 – 200 EUR/kW) and storage costs (100 – 400 EUR/kWh). Positive IRR indicates profitable investment assuming constant annual cash flows from day-ahead market arbitrage.

technologies. T2 takes the largest share at 36 %. However, all three technologies, T1, T2, and T3, earn reduced specific annual revenues compared to the 2 GWh scenario. This reflects cannibalization effects between FOs, as total revenue increases by only a factor of 2.1 despite tripled capacity. These effects are clearly visible when looking at revenue per installed MW and revenue per installed MWh. In general, competition between FOs has limited impact on individual technologies when total capacity remains relatively small, allowing T1 to improve its position. However, once total capacity increases significantly, revenue potential decreases sharply, with T1 experiencing the greatest relative losses compared to its competitors T2 and T3. This analysis demonstrates the critical importance of market saturation effects in determining FO profitability under competitive conditions.

4. Discussion

The following elaboration on limitations provides the necessary context for interpreting the findings presented, while establishing a foundation for future research to build upon this analytical framework. Our study focuses exclusively on endogenously simulated DAM revenues in Germany without considering additional revenue streams for the FOs or comprehensive cross market optimization strategies, in contrast to approaches based on exogenous historical price time series [64]. At present, such an integrated approach is beyond the scope of this paper, but would be of high interest [52]. In our analysis, the DAM serves primarily as a benchmark rather than providing a complete profitability assessment. This approach may underestimate total FO revenue potential. However, as FO capacity increases, additional revenue streams like

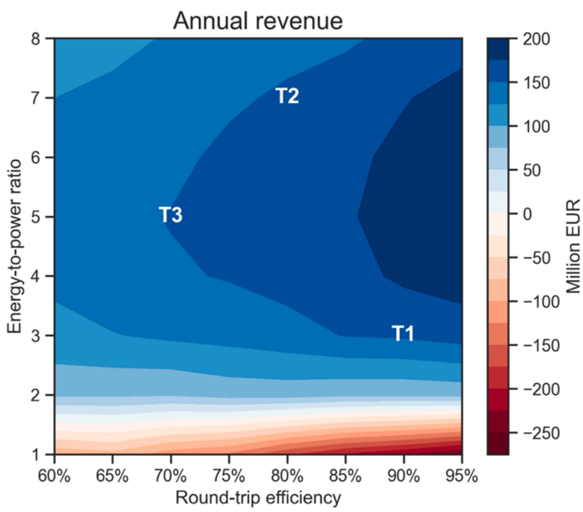

Fig. 11. Annual day-ahead market revenue (EUR/year) for a single battery storage system with fixed capacity of 6 GWh, as a function of energy-to-power ratio (E2P, x-axis) and round-trip efficiency (RTE, y-axis). Results are based on the 2030 Ariadne scenario with opportunistic strategy and machine learning forecasts. Markers T1 (E2P 3, RTE 90 %, representative of a battery storage system), T2 (E2P 7, RTE 80 %, representative of pumped hydro storage), and T3 (E2P 5, RTE 70 %, representative of a heat/air storage system) indicate the three configurations selected for the heterogeneous competition analysis.

intraday and reserves markets may also be impacted by cannibalization effects once dominated by FOs [33,65]. The ongoing transition of the European Day-Ahead Market (DAM) to 15-minute intervals may create additional arbitrage opportunities.

Our findings complement long-run equilibrium and capacity expansion studies, while challenging conclusions derived from price-taker or perfect-foresight assessments of short-run storage profitability. For example, [30] identify increasing revenue potential for systems with an E2P ratio of 1 in French scenarios using equilibrium modeling with price-taker assumptions, suggesting that RE variability compensates for price dampening effects from multiple FOs. In contrast, our endogenous price modeling reveals that high-powered systems, i.e., low E2P ratios, can face significant profitability challenges due to market price impacts which cannot be captured by studies with price-taker assumptions. As noted in Section 3.2, the ROI values reported in this study represent upper bounds that do not account for operation and maintenance costs or degradation costs. Other work demonstrates that cycle-induced degradation can reduce annual net profit of grid-scale storage by up to 24 % [66], an effect that scales directly with cycling frequency and therefore bears asymmetrically on the opportunistic strategy relative to the conservative one.

Our presented workflow couples ML with electricity market modelling, and confirms that incorporating future covariates significantly improves prediction accuracy, thus increasing storage revenue potential, consistent with findings by [40]. The selection of input data and hyperparameters proves essential for forecast accuracy [67], while the choice of the actual forecasting method clearly impacts simulated electricity prices, storage activity, and resulting profits [68]. These insights underscore the critical importance of high-quality price forecasting for FO operation, though comprehensive analysis of forecasting quality and its impact on competitive FO performance remains an area for future enhancements. While [65] also employ ML for electricity price prediction followed by dynamic programming for pumped hydro storage dispatch optimization, they neglect the system-wide feedback effects of storage operation, which our integrated approach explicitly captures.

While the quantitative analysis focuses on a German electricity market scenario, justified by the unprecedented battery storage connection requests, the methodological framework is directly transferable to other electricity markets operating under uniform pricing. In a cross-European analysis, [69] identify optimal E2P ratios of around 5 in solar-rich countries (e.g., Italy or Spain) and around 2–3 in wind-rich countries (e.g., Great Britain or Ireland) for BSS, which is broadly in line with our findings here. Assessments of BSS co-located with wind generation confirm that profitability remains sensitive to storage cost assumptions, with substantial cost reductions required to reach profitability [70].

Other literature suggest that BSS costs remain too high for widespread deployment, with profitable operation limited to approximately 4 % of peak demand [71]. In our study of the German market zone in a 2030 scenario, this threshold corresponds to roughly 4.7 GWh of total capacity. Our analysis reveals scenarios where FOs are profitable beyond this point, indicating that cost reductions and favorable market conditions could enable larger-scale deployment. However, we observe cannibalization effects in scenarios with FO capacities well below levels indicated by recent battery storage connection requests to German TSOs.

As with other studies on energy systems analysis [72], significant challenges stem from uncertainty regarding future system design and scenario parameters. Our analysis employs a full simulation year capturing hourly to seasonal variability while neglecting inter-annual weather variations, limiting the robustness of our profitability assessments. Furthermore, no variations of other parameters that impact

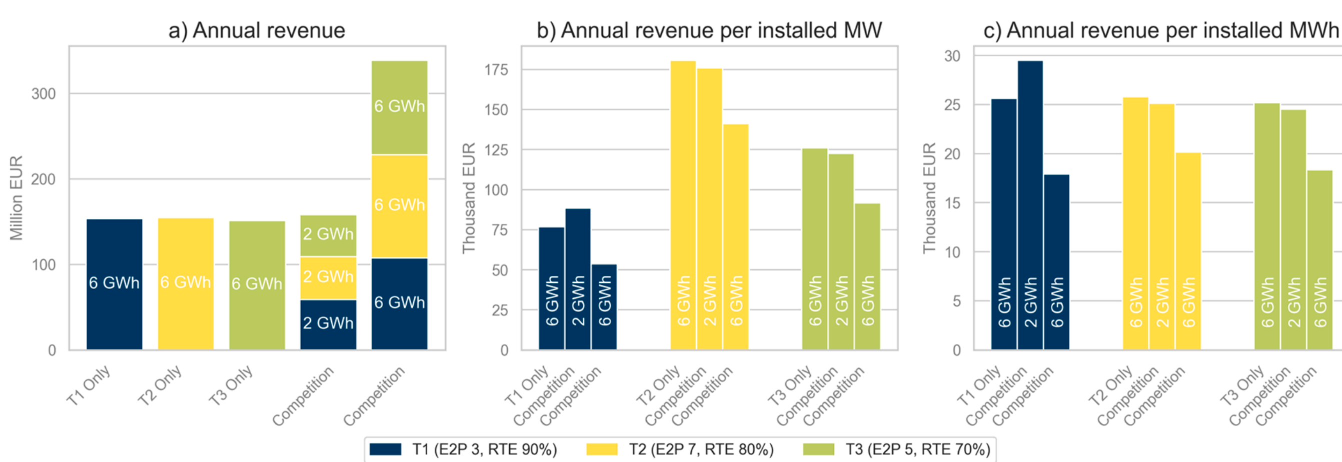

Fig. 12. Annual day-ahead market revenue (EUR/year) for three heterogeneous storage technologies T1 (E2P 3, RTE 90 %, representative of a battery storage system), T2 (E2P 7, RTE 80 %, representative of pumped hydro storage), and T3 (E2P 5, RTE 70 %, representative of a thermal storage system) operating individually and in direct competition at two total capacity levels (2 GWh and 6 GWh). Revenue per installed MW and per installed MWh are shown alongside total revenue to illustrate cannibalization effects.

electricity prices were performed here, e.g., emission allowance prices, fuel prices, electricity demand, hydrogen demand, power plant park, or market designs. For a comprehensive investment assessment, appropriate variations of these parameters should be considered. Regarding the market design, some studies suggest that RE and FO-dominated markets can function within energy-only market designs [73], others argue that wholesale revenues alone may inadequately incentivize necessary FO capacity expansion [74]. It is important to keep future studies up to date with market design developments. The dynamic nature of energy system transformation necessitates continuous model development [75]. To address this requirement, we have put strong efforts in research software development by adhering to FAIR principles [76]. Our open modelling workflow enables further expansion and adaptation by the research community, promoting reproducibility and facilitating extensions.

5. Conclusion

This paper advances the understanding of flexibility option profitability in future energy systems through a novel methodological approach that addresses critical gaps in existing literature. By coupling machine learning based electricity price forecasting with agent-based electricity market simulation, we provide a new assessment technique of flexibility option profitability that endogenously captures market price impacts and competitive dynamics. Our analysis, based on the Ariadne scenario targeting the German market zone, reveals several key insights for flexibility option deployment and investment opportunities. We demonstrate that the most profitable energy-to-power ratios for homogeneous battery storage systems fall between 4 – 8, differing from ratios identified in studies that treat electricity prices as exogenous inputs. This finding highlights how market price feedback fundamentally affects technical specifications, making operational strategies which account for price impacts necessary, especially for high-powered systems. The investigation of heterogeneous flexibility option competition reveals critical saturation effects where increased deployment leads to revenue cannibalization. When total flexibility option capacity triples from 2 GWh to 6 GWh, total market revenue increases by only a factor of 2.1, demonstrating diminishing returns that could significantly impact investment viability. Risk affinity in terms of opportunistic or conservative strategies influences revenue generation and charge cycle frequency, thereby affecting both profitability and storage lifetime considerations.

Beyond addressing the methodological limitations outlined previously, future research should prioritize two critical areas to enhance model comprehensiveness. First, incorporating endogenous intraday market modelling would enable comprehensive cross-market revenue assessment for flexibility options. Current focus on day-ahead markets provides valuable baseline insights but may underestimate total profitability by neglecting shorter-term trading opportunities where flexibility providers can capitalize on real-time supply-demand imbalances. This extension would be particularly relevant as intraday markets grow in importance within high renewable energy systems, where forecast errors and variability create additional arbitrage opportunities. Second, expanding the analysis of competitive dynamics between heterogeneous flexibility options represents an important research avenue. Extended analysis incorporating diverse operational strategies, energy system variations, and inter-annual weather time series would yield deeper understanding of future market dynamics. This would contribute to how different flexibility technologies, including battery storage systems, pumped hydro storage, demand response, and sector coupling, interact, compete, and potentially create synergistic effects under varying market conditions.

Code and data availability

All code used to run this analysis is openly available: the AMIRIS market model [39], the FAME simulation framework [44,45], and the AMIRIS-PriceForecast module [55]. The data is based on [42].

CRediT authorship contribution statement

Felix Nitsch: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Christoph Schimeczek:** Writing – review & editing, Supervision, Software, Investigation, Funding acquisition. **Valentin Bertsch:** Writing – review & editing, Supervision, Conceptualization.

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

Figs. 13–15.

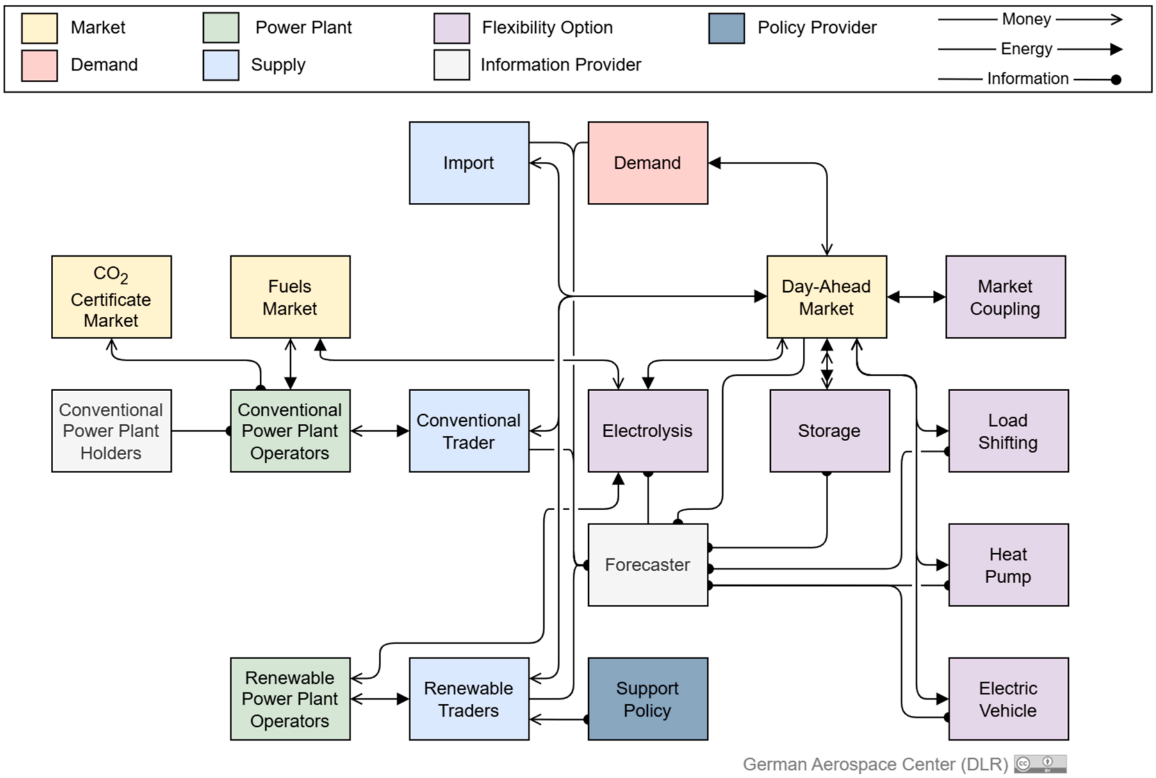

Fig. 13. Architecture of the open agent-based electricity market model AMIRIS [39], showing the main agent types (power plant operators, traders, market operator, and flexibility option operators) and their interactions through flows of information (arrows), energy, and money. Each agent type operates on individual rationality and information sets; market outcomes emerge from their collective interaction.

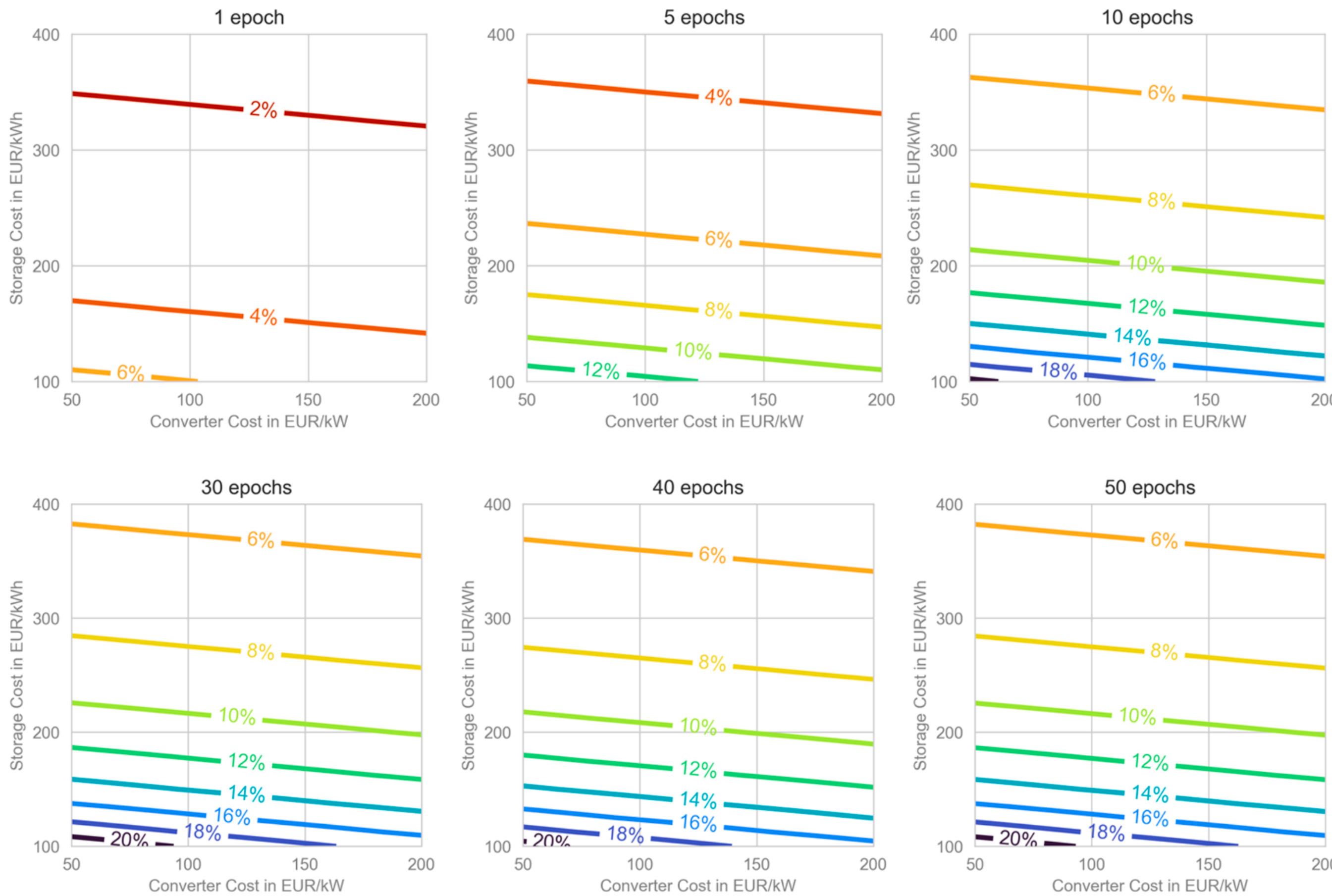

Fig. 14. Effect of machine learning model training duration (number of epochs) on the annual return on investment (ROI, %) of a 6 GW and 32 GWh battery storage system in the 2030 Ariadne scenario. Results indicate that the Temporal Fusion Transformer converges within approximately 10 epochs when trained on 30 scenarios of 8760 time steps each, with negligible further improvement at higher epoch counts.

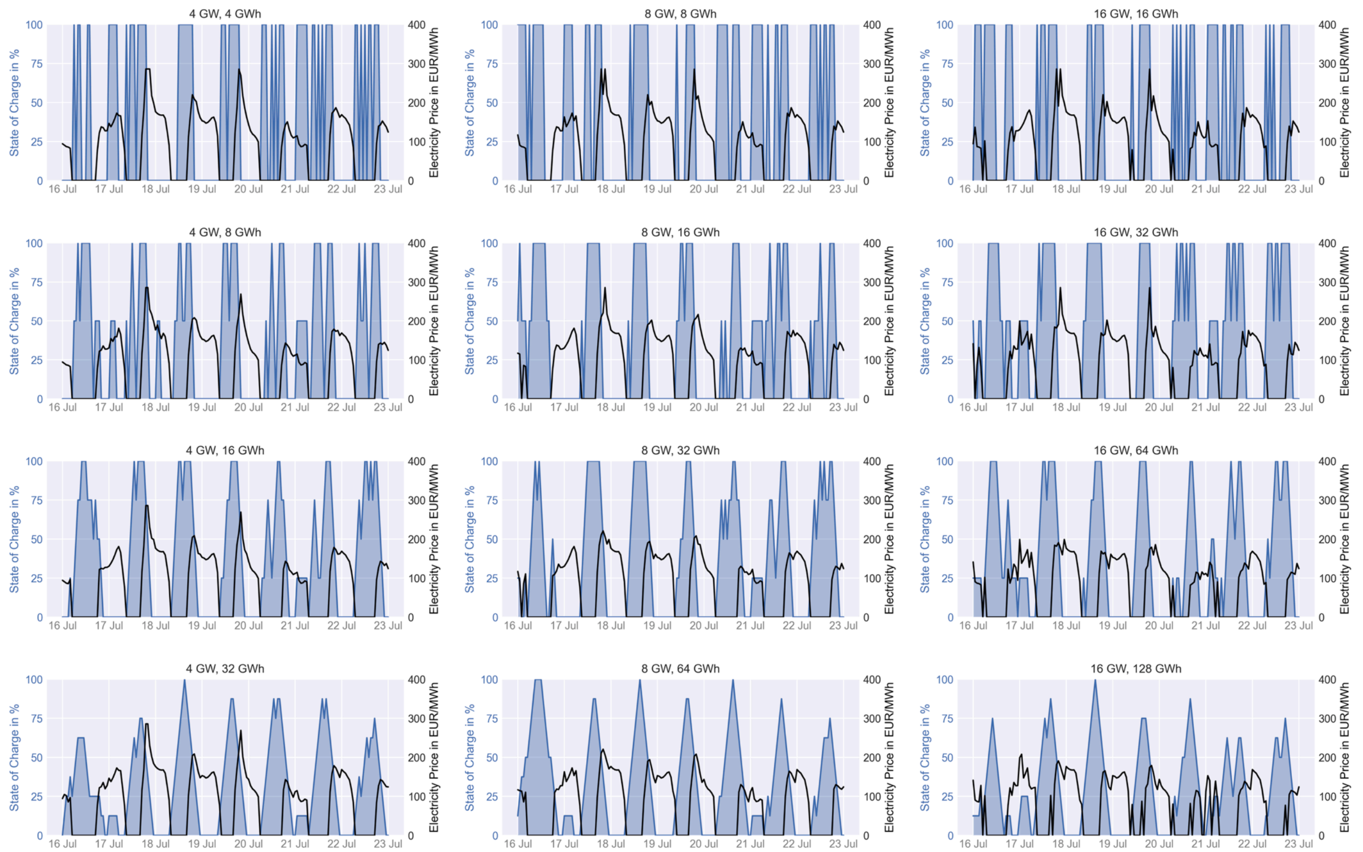

Fig. 15. State of charge (blue area, MWh) and day-ahead electricity price (black line, EUR/MWh) during a representative simulation week for storage systems spanning a range of energy-to-power ratios and round-trip efficiencies. Extended zero-price periods around noon result from high renewable generation exceeding demand; storage systems charge during these low-price hours and discharge during morning and evening price peaks to capture arbitrage opportunities. Differences in dispatch behavior across configurations illustrate how the energy-to-power ratio determines the ability to exploit multi-hour price spreads.

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