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Maximizing Profits in Electricity Markets: Optimizing Quantile-Based Trading with Energy Storage Systems

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Abstract

Effectively integrating renewable energy sources into electricity markets is essential to aligning real-time supply with demand and reducing revenue losses from curtailment. Storage technologies offer an effective means to overcome this issue by boosting grid reliability and operational efficiency, while also enhancing market liquidity and dampening price fluctuations. In short-term electricity markets, participants face a wide range of choices, each with distinct risks and benefits, and well-designed trading strategies are crucial for profit maximization. This research investigates the optimization of trading activities in the day-ahead and balancing markets of the Irish electricity system over the period 2019–2022, using quantile-based forecasting techniques. By applying three trading strategies subject to realistic operational constraints, the study assesses different approaches, raises trading frequency, and incorporates flexible timestamp-based orders. The results highlight substantial profit opportunities from concurrent participation in both day-ahead and balancing markets, particularly with larger battery storage capacities. Even though higher trading volumes entail greater costs and compressed profit margins, the adoption of adaptive dual-market strategies proves instrumental in maximizing returns and overcoming market-specific obstacles. Lastly, a scenario-based analysis assesses the economic feasibility of four commercial battery storage systems, demonstrating that larger battery units deliver shorter payback periods.

Keywords Machine learning, Electricity price forecasting, Energy storage systems, Arbitrage trading

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Introduction

The 21st century faces the task of integrating variable renewable energy sources into electricity systems. Electricity markets across Europe have witnessed a dramatic rise in variable renewable output, propelled by supportive policies and renewable energy targets [1]. Over the last ten years, worldwide deployment of wind and solar energy has shown consistent growth. In Ireland, the proportion of renewable generation in the electricity mix has grown rapidly, increasing from 21.7% in 2014 to 39.5% in 2022 [2]. Such extensive penetration can create instability in net power availability due to sudden, unpredictable variations in renewable production, which may raise concerns about system reliability [3].

This large-scale integration generates volatility in electricity markets due to abrupt, unexpected shifts in renewable generation, leading to economic inefficiencies and difficulties maintaining supply–demand balance [3]. Curtailment of excess renewable output during periods of low demand exemplifies these inefficiencies, causing forgone revenue and placing considerable financial strain on the market. In Ireland, curtailment levels—shown in **Figure 1**—fluctuate between 3.0% and 5.9%, suggesting that pursuing further capacity expansion may become counterproductive and impose

substantial economic costs. A recent analysis identified Ireland as having the highest curtailment rate among the examined countries [4], prompting greater research efforts to improve renewable energy integration.

To mitigate these issues, contemporary electricity markets are increasingly using Battery Energy Storage Systems (BESS) as a key mechanism to reduce supply and demand imbalances stemming from renewable energy variability. BESS offers a viable approach to overcome these constraints by improving the effective use of renewable energy and cutting curtailment-related losses. Thoughtful implementation of BESS helps alleviate network constraints, increases financial returns from renewable assets, and strengthens overall grid stability. Moreover, the financial impact of curtailment—especially the revenue foregone due to insufficient demand—emphasizes the urgent requirement for robust energy storage options. Tackling these difficulties via market-based mechanisms promotes a more robust and efficient energy framework, facilitating deeper penetration of variable renewable sources.

The growing adoption of Battery Energy Storage Systems (BESS) highlights the growing focus on generating revenue through energy arbitrage [5]. BESS facilitates effective energy shifting by capitalizing on price differences between off-peak and peak periods, thereby decreasing dependence on expensive, rapid-response generation sources such as thermal peaker plants. In addition, BESS supports load shifting, enhanced power quality, and overall grid stability. BESS integration has increased within the Single Electricity Market (I-SEM), encompassing the spot markets, specifically the Day-Ahead Market (DAM) and the Balancing Market (BM). The DAM enables energy trading for delivery on the following day via daily auctions, whereas the BM functions as the “market of last resort,” correcting real-time mismatches between supply and demand.

In contrast to the DAM, the BM operates at much higher resolution, requiring near-immediate responses to system imbalances caused by demand fluctuations, unexpected generator failures, and the variable characteristics of renewable generation [6, 7]. This poses particular difficulties in Ireland, where wind power—a primary renewable source—creates substantial volatility owing to its unpredictable nature [8]. The Irish BM relies heavily on the flagging and tagging mechanism, a distinctive procedure that ensures only energy-related balancing actions affect imbalance prices, excluding influences from system security requirements [9]. These mechanisms ensure precise price signals in the BM while preserving grid stability.

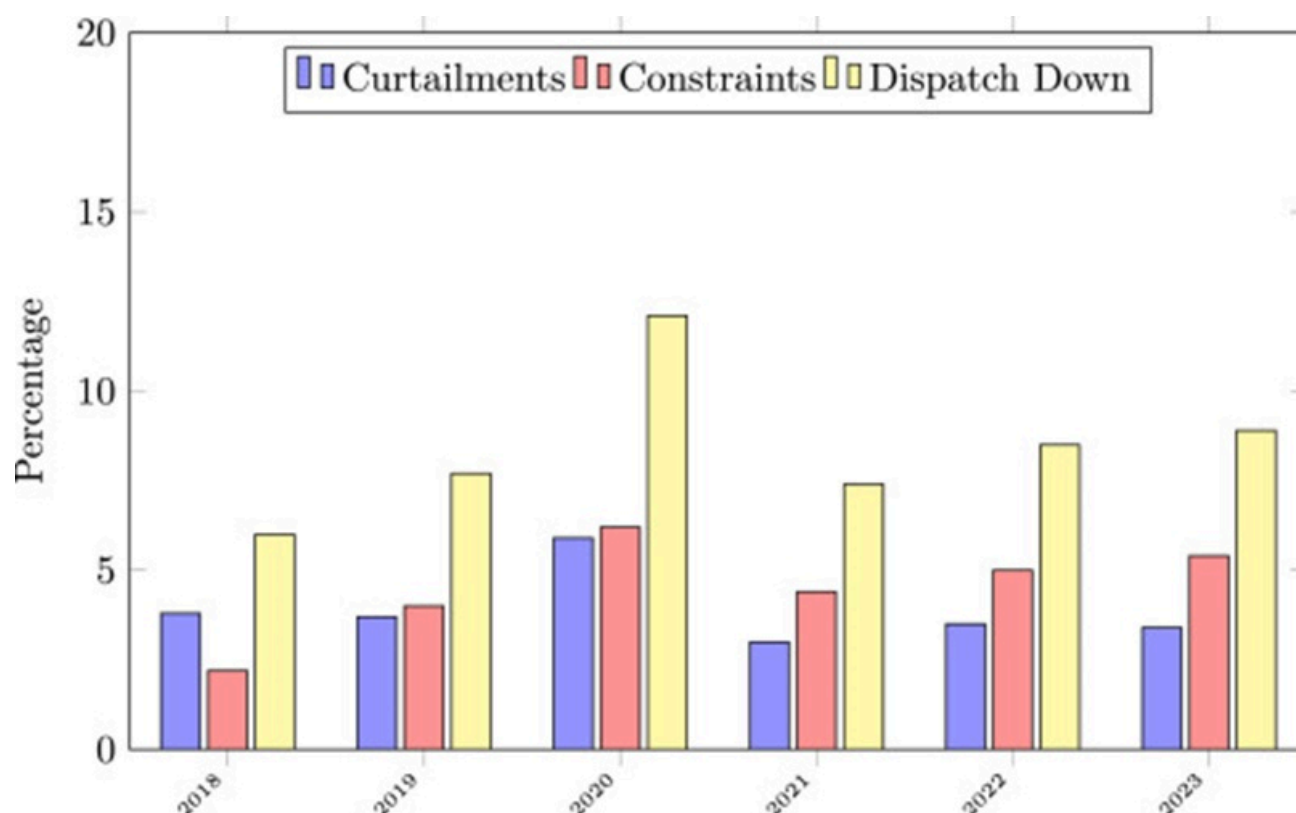


Figure 1. Annual percentages of curtailments, constraints, and dispatch down incidents, illustrating the impact of renewable energy challenges on wind output [10].

Compared with other European balancing markets, such as those in Germany and the Iberian Peninsula, the Irish BM operates in a smaller, more isolated grid, which magnifies the effects of forecasting inaccuracies and renewable intermittency. In Germany, for example, the BM gains advantages from stronger grid interconnections and broad cross-border collaboration, enabling better management of imbalances via shared resources [11]. Likewise, the Iberian BM adopts a coordinated strategy for renewable integration, drawing on its varied energy portfolio and regional market framework. In comparison, the Irish BM's structure must address its grid limitations and elevated renewable share by implementing more localized balancing solutions. As renewable generation expands further, precise real-time forecasting of supply–demand discrepancies grows ever more essential for the Irish market, particularly to support efficient BESS arbitrage and bolster market resilience amid volatile conditions [6, 12]. Successful BESS arbitrage in such markets depends critically on reliable probabilistic electricity price forecasting (PEPF), which boosts profitability and reduces risk exposure [13].

Contributions

In this paper, we address emerging research directions that extend past conventional PEPF evaluation metrics—focused on reliability, sharpness, and resolution—to incorporate trading strategies for improved forecast benchmarking. Our work examines trading in the DAM and BM using probabilistic forecasting, contributing to fill key gaps in the current literature, specifically:

- We present a thorough trading framework that accounts for realistic BESS limitations, such as battery capacity, ramp rates, round-trip efficiency, buy–sell order limitations, and state-of-charge boundaries, to assess the practical value of PEPF across both markets. We also deliver a versatile Python-based tool to enable scenario testing and examine how these constraints influence profitability, linking theoretical frameworks to real-world market implementations.

- We lower barriers for researchers by releasing publicly available datasets covering the DAM and BM. These resources enable model testing and strategy evaluation, promoting wider engagement in electricity price forecasting research, with special attention to the less-studied BM. They also facilitate advanced techniques such as transfer learning. Additional information and dataset access are provided on GitHub.¹
- Our research progresses trading methodologies through a novel dual-market lens, utilizing real-time forecasting that concurrently targets both the DAM and BM. Departing from prior works that frequently neglect realistic BM forecast horizons, we synchronize DAM decisions with BM commitments via more practical 8-hour BM forecasts, yielding feasible and effective strategies that maximize profits.
- We assess the financial viability of four commercial BESS configurations over a 15-year scenario analysis. This encompasses an in-depth evaluation of costs, revenues, and changing market dynamics to inform investment choices.
- Overall, we investigate the capabilities of quantile-based forecasts in energy markets, stressing battery sizing, trading approaches, and economic attractiveness to equip participants for success in fluctuating electricity markets.

Literature Review

This section reviews the pertinent literature on electricity price forecasting and associated trading strategies.

Probabilistic forecasting

Probabilistic Electricity Price Forecasting (PEPF) plays a vital role in energy markets, focusing primarily on price prediction while drawing on supporting forecasts of load demand, wind power, and solar output. It helps manage uncertainties arising from factors like smart grid deployment, renewable energy integration, and the growing presence of electric vehicles [14, 15]. Recent research has thoroughly examined best practices and appropriate evaluation metrics [16]. Nowotarski and Weron [17] reviewed multiple methodologies, including autoregressive models, neural networks, quantile regression averaging, and ensemble techniques. They discuss evaluation metrics such as pinball loss and interval score, emphasizing reliability, sharpness, and strict out-of-sample validation. Marcjasz *et al.* [18] integrated deep learning approaches into PEPF, demonstrating the advantages of models that account for seasonal patterns. Tzallas *et al.* [19] proposed a computationally efficient model tailored for forecasting UK electricity prices. Marcjasz *et al.* [20] underscored the value of forecast combination for greater accuracy, especially when using distributional deep neural networks. Monjazebe *et al.* [21] demonstrated the effectiveness of quantile regression (QR) in capturing price uncertainty in pay-as-bid market structures across diverse regional and weather conditions. Uniejewski and Weron [22] proposed LASSO Quantile Regression Averaging (QRA), a technique that refines point forecasts by combining quantile regression with LASSO regularization; they later enhanced QRA with kernel-based smoothing [23], achieving superior performance relative to benchmarks across reliability, precision, and economic outcomes. Jiang *et al.* [24] and Zakrzewski *et al.* [25] developed nonconvex regularized QRA and Factor QRA methods to improve the accuracy of electricity price forecasting (EPF), with particular gains in probabilistic settings. Janczura [26] introduced Expectile Regression Averaging as a competitive alternative to conventional quantile-based methods such as QR and QRA, achieving better accuracy for EPF in the Day-Ahead Market (DAM).

Research on probabilistic forecasting specifically for the Balancing Market (BM) remains limited, primarily due to difficulties in obtaining suitable data. Klæboe *et al.* [27] compared state-dependent models (such as SARMA and ARM) against standard time-series models (ARMA and ARX), finding that the inclusion of contextual variables improved forecast quality. Nonetheless, these studies typically cover short forecast horizons, often no more than one hour ahead, leaving longer-term BM forecasting largely unaddressed. In the Belgian market, Dumas *et al.* [28] developed an approach for imbalance price prediction based on historical records, transition probabilities of net regulation volume, and reserve activation details. Other work, such as that of Bunn *et al.* [29], has explored the predictability of BM prices through regime-switching models, indicating that BM prices exhibit forecastable patterns and questioning the notion of full market

efficiency. These findings imply meaningful opportunities for participants to build forecasting and trading strategies rooted in solid econometric foundations. Furthermore, Lucas *et al.* [30] applied machine learning methods to BM price forecasting in Great Britain, revealing strong performance from Gradient Boosting and Extreme Gradient Boosting algorithms. Conversely, Narajewski [31] studied BM prediction in the German electricity market and found that simpler models often outperformed more complex ones.

Energy storage

Recent reforms in European electricity markets emphasize the development of robust mechanisms to accommodate the growing integration of renewable energy sources [7]. The economic feasibility of energy storage systems within electricity markets has been investigated across multiple settings. Staffell and Rustomji [32] examined the profitability of energy storage in the British market, highlighting the importance of revenue streams from reserve services. Tohidi and Gibescu [33] assessed the potential earnings from flow battery storage integrated with photovoltaic (PV) solar installations, accounting for uncertainties in both electricity prices and PV generation. Abramova and Bunn [34] focused on trading and optimization strategies for battery storage to improve financial returns. Gräf *et al.* [35] studied battery pack degradation, with particular attention to the effects of temperature fluctuations. On average, degradation occurred at 1.55% per year, with temperature-dependent annual rates ranging from 1.03% to 2.00%. Wankmüller *et al.* [36] incorporated the influence of degradation into arbitrage profitability calculations. More recently, Elalfy *et al.* [37] emphasized the advantages of hybrid energy storage systems (ESS) in boosting performance, especially for supporting renewable integration and grid stabilization—objectives that align closely with the dual-market strategies examined in this study. Likewise, Amir *et al.* [38] developed optimal scheduling frameworks and sustainable policy recommendations to tackle both economic and environmental issues, providing valuable guidance for deploying energy storage in fluctuating market conditions. Hu *et al.* [39] evaluated the economic prospects of Battery Energy Storage Systems (BESS) across European electricity markets, concluding that although high costs currently constrain energy arbitrage, BESS offers considerable potential for frequency regulation services, particularly in less flexible markets such as Ireland.

Trading

In energy trading, developing profitable strategies for energy storage systems depends heavily on accurate probabilistic forecasts. Krishnamurthy *et al.* [40] conducted an in-depth review of trading models designed for arbitrage in both the Day-Ahead Market (DAM) and Balancing Market (BM), demonstrating the clear advantages of stochastic approaches under conditions of price uncertainty. Their proposed models—a Quantity-Only bid model and a Price-Quantity bid model—differed in profitability and risk exposure. In a related study, Narajewski and Ziel [41] explored optimal bidding strategies in auction-based electricity markets, focusing on portfolios dominated by renewable energy sources. Their findings stressed the importance of accounting for market impact and transaction costs when determining optimal strategies for risk-neutral participants. The study covered diverse portfolios, including those of wind and solar producers, and illustrated significant revenue gains achievable even with straightforward forecasting techniques. Recent progress in electricity trading strategies has increasingly combined machine learning with conventional optimization techniques to enhance scalability, flexibility, and decision-making in uncertain environments. Multistage stochastic programming, as investigated by Silva *et al.* [42], accounts for future price trajectories and storage system behavior across multiple time steps, enabling ongoing strategy refinements to handle market volatility and operational constraints. Despite their effectiveness, such methods can struggle with non-linear relationships and large-scale data. To overcome these limitations, machine learning approaches have been adopted to boost computational performance and scalability. However, challenges related to parameter sensitivity and the lack of strong theoretical guarantees may limit their use in regulated settings [43].

Mixed-Integer Linear Programming (MILP) has become a prominent technique for risk management and strategy optimization across different markets. It is frequently employed in energy storage optimization because it effectively models mutually exclusive constraints, such as the inability to charge and discharge simultaneously [44]. Recent research by Kraft *et al.* [45] illustrates the adaptability of MILP in reconciling profit-maximizing, risk-neutral strategies in the intraday market (IDM) with risk-averse strategies in the DAM that reduce exposure to price swings. Similarly, integrating

reinforcement learning and dynamic programming, as discussed by Alghumayjan *et al.* [46], improves real-time trading performance through adaptive decision-making. These methodologies support aligning renewable energy storage systems with evolving market structures, ultimately contributing to greater grid reliability and economic returns [47].

While these methods offer considerable advantages, our research emphasizes computational efficiency and real-world usability by adopting alternative probabilistic techniques better suited to the demands of real-time forecasting in fast-changing markets. In particular, substantial gaps persist in applying probabilistic forecasting methods to the Balancing Market (BM), where shorter prediction windows and greater price volatility create significant practical difficulties. By addressing these limitations and synchronizing BM decisions with Day-Ahead Market (DAM) strategies, our work delivers a robust framework that enhances forecast reliability and improves performance in dual-market trading.

Datasets

The dataset supporting this research combines market and battery-related information, enabling a thorough assessment of trading strategies and the long-term economic feasibility. All input data were obtained from SEMO and SEMOpX, covering historical records and forward projections spanning 2019 to 2022. The dataset is divided into two primary categories: historical data and forward/future-oriented data. Battery specifications include technical characteristics, cost details, and degradation factors, facilitating scenario evaluations over 10–15-year timeframes.

Day-ahead market

Our analysis centers on forecasting DAM prices, with the prediction window beginning at time t and covering the next 24 settlement periods, expressed as:

$$Y_{DAM} = [DAM_t, \dots, DAM_{t+23}]. \quad (1)$$

Bids for the DAM are submitted by 11:00, with prices published at 13:00, and trading runs for 24 hours from 23:00 on the current day to 23:00 on the following day.

Forward-looking data

Forward-looking data enables the model to anticipate DAM prices based on anticipated supply and demand patterns. The included variables are:

- Demand Forecast (DF) in MWh: 24-hour demand projections supplied by the TSO, reflecting daily and seasonal usage patterns that directly affect market prices: $[DF_t, \dots, DF_{t+23}]$.
- Wind Generation Forecast (WF) in MWh: 24-hour wind power projections from the TSO, accounting for renewable intermittency—a major contributor to price fluctuations in markets such as the I-SEM: $[WF_t, \dots, WF_{t+23}]$.

Historical data

Historical records enable the identification of patterns and dynamics essential for accurate DAM price prediction. The dataset comprises:

- DAM Prices (DAMP) in €/MWh: Prices from the prior 7 days (168 hours) to reflect recent market behavior: $[DAMP_{t-167}, \dots, DAM_{t-1}]$.

- Past Wind Forecasts (PWF) in MWh: TSO wind forecasts from the previous 7 days, capturing the effects of wind variability: $[PWF_{t-167}, \dots, PWF_{t-1}]$.

Balancing the market

For the BM, we forecast BM prices across the next 16 open settlement periods. The forecast horizon commences at $t + 2$, since at time t the periods t and $t + 1$ are already settled, permitting adjustments only from $t + 2$ onward, denoted as:

$$Y_{BM} = [BMP_{t+2}, \dots, BMP_{t+17}]. \quad (2)$$

Forward-looking data

Forward-looking data provides a predictive perspective on market conditions, which is essential for forecasting BM prices. The dataset comprises:

- Physical Notifications Volume (PHPN) in MWh: Anticipated adjustments in generation or consumption across the forecast window, which shape balancing requirements: $[PHPN_{t+2}, \dots, PHPN_{t+17}]$.
- Net Interconnector Schedule (PHI) in MWh: Forecasted cross-border electricity transfers, impacting overall supply–demand equilibrium: $[PHI_{t+2}, \dots, PHI_{t+17}]$.
- Renewable Forecast (PHFW) in MWh: TSO projections of renewable generation (primarily wind and solar), crucial given their inherent variability: $[PHFW_{t+2}, \dots, PHFW_{t+17}]$.
- Demand Forecast (PHFD) in MWh: Projected electricity usage, highlighting potential periods of scarcity or oversupply: $[PHFD_{t+2}, \dots, PHFD_{t+17}]$.
- DAM Prices (DAM) in €/MWh: Forward DAM prices covering the next 8 hours, reflecting anticipated supply–demand conditions: $[DAM_{t+1}, \dots, DAM_{t+16}]$.

Historical data

Historical data records previous market patterns to guide predictions of future price behavior. The dataset includes:

- Balancing Market Prices (BMP) in €/MWh: BM prices from the most recent 24 hours, capturing prevailing trends and volatility: $[BMP_{t-51}, \dots, BMP_{t-3}]$.
- Balancing Market Volume (BMV) in MWh: Volumes traded for system balancing over the preceding 48 periods: $[BMV_{t-51}, \dots, BMV_{t-3}]$.
- Forecast Wind - Actual Wind (WDiff) in MWh: Differences between predicted and realized wind output during the last 48 periods, a major source of price fluctuations: $[WDiff_{t-51}, \dots, WDiff_{t-3}]$.
- Interconnector Flows (I) in MW: Cross-border power transfers over the past 48 periods, affecting local price formation: $[I_{t-50}, \dots, I_{t-2}]$.
- DAM Prices (DAM) in €/MWh: Recent 24-hour DAM prices adjusted to align with half-hourly settlement intervals: $[DAM_{t-48}, \dots, DAM_t]$.

The differing time spans for historical variables stem from data availability constraints, which limit them to the most recent 48 observations from the source. For additional information on our forecasting methodology, market framework, datasets,

and variables used for both the DAM and BM, refer to O'Connor et al. [48] and GitHub.²

Battery configurations

Battery-related data encompasses technical parameters, capital and operational expenditures, and maintenance costs for four distinct commercial setups. These inputs enable long-term scenario modeling of Battery Energy Storage Systems (BESS) spanning 10–15 years. **Table 1** provides a summary of the principal specifications and cost elements for the modeled batteries: Capital expenditure (CAPEX) covers acquisition, installation, commissioning, and associated expenses, while operations and maintenance (O&M) includes fixed and variable components, projected to increase by 2% each year. Degradation is modeled at an annual rate of 1.55%, consistent with lithium-ion battery performance data, with an operational life expectancy of 10–15 years. Fees for market registration in the I-SEM are also factored in. This dataset underpins the scenario evaluations and profitability assessments, delivering valuable insights into the economic attractiveness of different BESS configurations and trading approaches. Further details are available in Baxter and Byrne [49] and Herzer [50].

Table 1. Battery specifications and costs.

Battery attribute	Scottish power	Tesla megapack	Avolta storage	Tesla megapack (x10)
Capacity (MWh)	3.0	3.9	10.0	38.5
Cycle duration (h)	1	2	1	2
Efficiency (%)	95	95	95	95
CAPEX (€/kWh)	557	447	485	356
Annual O&M (€/kWh)	4	2	10	2
Profitability year	12	11	11	7
15-year return (%)	16	34	38	123

Materials and Methods

This section describes the methodological framework employed in our study to develop trading strategies for Battery Energy Storage Systems (BESS). These strategies involve the optimization—and in certain cases, co-optimization—of revenue opportunities from participation in ancillary service markets, energy-only markets, or a combination of both, while clearly distinguishing these activities from the balancing charges imposed by the Transmission System Operator (TSO) on Balance Responsible Parties (BRPs). Much like ancillary service markets support grid stability and dependability, BESS are assuming a growing importance in facilitating the integration of renewable energy within the transforming energy sector. To fulfill this goal, our main focus is on designing trading strategies to maximize profits through energy arbitrage in the Day-Ahead Market (DAM) and the Balancing Market (BM).

Methodology overview

In our study, the forecasting and trading framework can be broadly structured into five main stages for both the Day-Ahead Market (DAM) and Balancing Market (BM). These stages are as follows:

1. Data Collection and Preparation: We compile historical and forward-looking data from the I-SEM relevant to the DAM and BM.

2. **Data Pre-processing and Model Optimization:** Before modeling, the data undergoes pre-processing. Each forecasting model is hyperparameter-optimized on every 3-month data segment to maximize predictive performance.
3. **Walk-Forward Model Validation:** To ensure model robustness, we use a walk-forward validation procedure that progressively advances the training window.
4. **Quantile Forecasting:** Optimized models generate quantile forecasts on unseen test data. For the DAM, these forecasts cover a standard 24-hour horizon. For the BM, models are retrained every 8 hours to integrate the latest observations while predicting the subsequent 16 settlement periods. This frequent retraining accommodates the BM's distinct characteristics, including elevated volatility and shorter decision windows, which necessitate regular model updates to sustain forecast quality. For a detailed comparison of the DAM and BM forecasting methodologies, refer to O'Connor et al. [48].
5. **Trading Strategy Execution:** Using the resulting quantile predictions, we execute the selected trading strategy. This entails placing quantity-based bids and offers in both the DAM and BM, consistent with the respective 24-hour and 8-hour forecast horizons.
6. **Economic Viability Assessment:** To evaluate the long-term feasibility of battery storage systems, we simulate trading profits over a two-year historical period and project these outcomes across a 15-year battery lifetime.

To ensure empirical validity, we implement a back-testing framework that compares forecasted results with actual market-clearing prices. This simulation replicates genuine trading environments, confirming the connection between forecast precision and trading outcomes. By purchasing electricity at times of low anticipated prices, storing it in the battery, and selling during high-price intervals, our approach illustrates the real-world effectiveness and economic potential of the proposed trading strategies under authentic market conditions.

Quantile regression models

All models employed in this research rely on quantile regression, a statistical method that estimates conditional quantiles of the target variable. This enables prediction at chosen quantile levels (e.g., 0.1, 0.3, 0.5, 0.7, 0.9). These quantiles form a “quantile pair”, $[\hat{q}\tau\alpha, \hat{q}\tau1-\alpha]$, defining a prediction interval with lower and upper bounds that reflect a specified confidence range. For example, pairing the 0.1 and 0.9 quantiles ($q\tau\alpha = 0.1$ and $q\tau1-\alpha = 0.9$) creates an interval that captures the central 80% of probable outcomes, offering a detailed view of the forecast distribution. See **Figure 2** for illustration.

The models can be grouped at a high level into the following categories:



Figure 2. Quantile forecast of electricity prices.

- **K-Nearest Neighbors (KNN):** A flexible non-parametric technique that estimates the target for a given instance by averaging the outputs of its “K” closest neighbors in the feature space, based on distance measures such as Euclidean or Manhattan. This method excels at detecting localized patterns in time-series datasets.
- **Random Forest (RF):** An ensemble approach widely applied in DAM and BM forecasting owing to its proficiency in managing non-linear relationships and high-dimensional inputs. By combining outputs from numerous decision trees, RF effectively models complex temporal dependencies and delivers stable predictions across both short- and longer-term horizons.
- **Light Gradient Boosting Machine (LGBM):** Similar to RF, gradient boosting techniques have become favored in DAM and BM tasks for their speed and scalability. As a boosting method, LGBM constructs decision trees sequentially, concentrating on hard-to-predict instances with large residuals to iteratively refine accuracy. This enables LGBM to identify subtle temporal structures while remaining computationally efficient.
- **Deep Neural Network (DNN):** A highly adaptable deep learning architecture with tunable hyperparameters. It effectively integrates historical records and forward-looking inputs for precise forecasting. A hybrid version combines LSTM layers with standard DNN components, improving performance by capturing sequential dependencies in past data alongside future-oriented features [51]. The model’s output layer produces predictions for 8 hours (equivalent to 16 timestamps). See Figure 3 for a visual representation.

We applied a uniform hyperparameter-tuning procedure using grid search with cross-validation. Pinball loss was selected as the primary loss function due to its direct correspondence with the goals of quantile forecasting. Tuning was conducted over successive rolling 3-month data windows, with model-tailored settings to promote robustness. For KNN, we optimized the number of neighbors and the distance metric to achieve an effective balance between flexibility and computational speed. For RF, adjustments were made to the number of trees and the maximum tree depth to balance

overfitting and generalization. LGBM hyperparameters—including learning rate and number of boosting rounds—were carefully adjusted to detect complex temporal dependencies better. At the same time, the DNN architecture was iteratively refined using Talos to optimize the balance between model complexity and predictive accuracy. A walk-forward validation scheme was implemented, in which models were trained on historical data and evaluated on subsequent unseen periods, mirroring actual forecasting conditions encountered in practice. For additional information on the hyperparameter tuning process and overall forecasting methodology for the models, refer to O'Connor et al. [48].

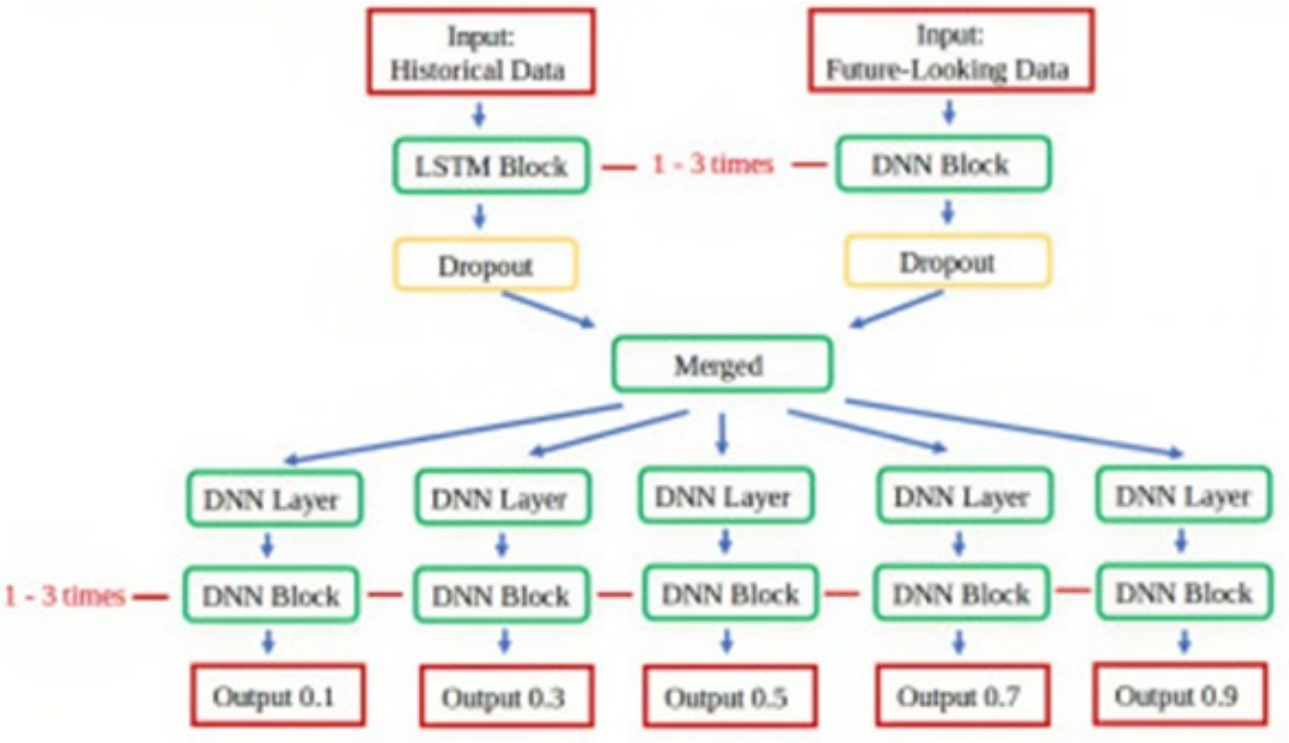


Figure 3. MH RNN DNN Model.

Trading strategies

This section introduces three trading strategies specifically designed to maximize profits in electricity markets while respecting operational constraints and price behavior patterns, including:

1. Trading Strategy 1 (TS1) employs a rule-based heuristic that follows a simple single-trade logic. This approach guarantees that the buy timestamp precedes the sell timestamp.
2. Trading Strategy 2 (TS2) retains the constraints of TS1 but enhances intraday trading activity through an iterative multi-trade procedure.
3. Trading Strategy 3 (TS3) employs an optimization-driven high-frequency method that permits flexible buy and sell timestamps, subject to bottleneck limitations on purchasable and sellable volumes.

These trading strategies are applied independently to the DAM and the BM. We describe a modified version that enables simultaneous position holding in both the DAM and the BM.

TS1: Single trade quantile strategy

TS1 is a heuristic, rule-based trading strategy adapted from Uniejewski and Weron [22] and Uniejewski [23], and it incorporates identical BESS constraints. It utilizes quantile-based forecasts to guide trading decisions for a notional battery characterized by capacity B_c , unlimited discharge rate, discharge efficiency η_d , and charge efficiency η_c . Within the relevant time horizon (24 hours for the DAM or 8 hours for the BM), only one buy–sell pair is allowed, with the explicit condition that the buy action precedes the sell action. This buy/sell sequencing constraint maintains logical trade consistency, reflecting the physical reality that a battery must first charge before it can discharge. The requirement is especially relevant when starting from a fully discharged state of charge and enforcing a logical sequence of charging followed by discharging. The main steps of TS1 are outlined below:

1. **Identify Optimal Timestamps:** Select the timestamps corresponding to the lowest predicted price at quantile q_t^α and the highest at the complementary quantile $q_t^{1-\alpha}$, choosing the pair that yields the largest price differential.
2. **Execute Trades:** Place buy and sell orders at the identified optimal timestamps.
3. **Calculate Profit:** Compute the profit as the difference between the sell price and buy price, adjusted by the charge efficiency η_c and discharge efficiency η_d .

The core aim of this strategy is to maximize anticipated profit by exploiting the quantile pair $[q_t^\alpha, q_t^{1-\alpha}]$, which is selected to identify promising arbitrage opportunities based on forecasted price distributions. The objective function for TS1 is expressed as:

$$\max \sum_{t=1}^T \left(\eta_d \cdot \hat{q}_{t_2}^\alpha - \frac{\hat{q}_{t_1}^{1-\alpha}}{\eta_c} \right) \quad (3)$$

Where $\hat{q}_t^\alpha$ denotes the predicted α -quantile price at time t , and $\hat{q}_t^{1-\alpha}$ represents the complementary $(1 - \alpha)$ -quantile price (the higher quantile forecast), used here to evaluate profitable trade opportunities. For DAM trading, the forecast covers a 24-hour horizon at hourly resolution, whereas BM trading uses an 8-hour horizon at half-hourly resolution, commencing 2 intervals after the current timestamp. This results in 24 time steps for the DAM and 16 for the BM. Refer to **Figure 4** for an illustration.



Figure 4. Aligned DAM and BM trading timelines with submission and trading details.

TS2: Multi-trade strategy

TS2 builds upon TS1 by iteratively locating multiple buy–sell pairs across the 24-hour horizon in the DAM or the 8-hour horizon in the BM, while preserving the requirement that buy timestamps precede sell timestamps and thereby increasing the frequency of intraday trades. The initial three steps of TS2 align with those of TS1. The additional three steps unique to TS2 are described below:

1. **Create Additional Price Subsets:** To respect the buy/sell sequencing constraint, the price series is partitioned into subsets. This segmentation is performed temporally, dividing the data into portions before and after the initial trade pair identified in TS1. Such division prevents overlap between trades and enables more effective exploitation of the available trading window.
2. **Identify Buy–Sell Pairs:** Within each resulting subset, the procedure mirrors TS1: locate the timestamps of the lowest predicted price at quantile $\hat{q}_t^\alpha$ and the highest at the complementary quantile $\hat{q}_t^{1-\alpha}$. The quantile pair helps balance potential reward against risk by pinpointing the most profitable price spread within that subset. For each identified pair, place buy and sell orders corresponding to the largest differential, while strictly enforcing the buy-before-sell rule.
3. **Calculate Profit:** For every valid trade pair, compute the profit as the difference between the sell and buy prices, adjusted for battery charging efficiency η_c and discharging efficiency η_d , following the same adjustment method as in TS1. The total profit for the strategy is obtained by summing the profits across all identified pairs from the various subsets.

Although TS2 generates more trading opportunities than TS1, its effectiveness is constrained by the requirement to sequence buy and sell orders.

TS3: High-frequency strategy

TS3, drawing on Staffell and Rustomji [32], adopts an optimization-driven framework designed to overcome the practical constraints imposed by battery ramp rates. These limitations are especially relevant for larger battery systems, where completing a full charge or discharge cycle within a single trading interval is generally impractical. By introducing a bottleneck mechanism, TS3 achieves considerably greater flexibility in selecting buy and sell timestamps, effectively eliminating the strict requirement that buy timestamps precede sell timestamps. In this study, the bottleneck incorporates several realistic operational constraints. The ramp rate R is limited by the battery's capacity and its maximum permitted charging speed, which restricts the amount of energy that can be absorbed in any given interval. Likewise, the discharging rate is constrained by the current state of charge and the maximum allowable discharge speed, influencing the volume of energy that can be released. The battery's overall capacity determines the total tradable energy volume. To preserve battery longevity and operational reliability, a minimum state-of-charge threshold is enforced.

Furthermore, round-trip energy efficiency losses (represented by E_d for discharge and E_c for charge) are accounted for during both charging and discharging phases. Together, these factors delineate the feasible operating envelope for the trading strategy and are essential to its realistic performance. The principal steps of TS3 are summarized as follows:

1. **Find Min and Max Price Periods:** Consistent with TS1 and TS2, identify the timestamps associated with the minimum predicted price at a chosen quantile ($\hat{q}_t^\alpha$) and the maximum predicted price at the complementary quantile ($\hat{q}_t^{1-\alpha}$). Unlike the earlier strategies, the relative ordering of these timestamps is no longer fixed.
2. **Charging/Discharging Bottleneck:** This phase addresses the charging and discharging constraints. Depending on whether the minimum-price period precedes or follows the maximum-price period, the algorithm dynamically configures charging and discharging actions to optimize profitability. A detailed explanation of the bottleneck handling and corresponding profit computations is provided in [Algorithm 1](#).

3. Iterate for Additional Trade Pairs: The same procedure is recursively applied to price data subsets located before, after, and between each previously identified trade pair, enabling the discovery of further arbitrage possibilities across different intervals.

4. Repeat for All Trade Pairs: The iteration continues across all remaining subsets until no additional viable buy and sell pairs can be identified.

```

1: Initialize variables:  $c$  (charge level),  $x_{buy}$  (charging quantity),  $x_{sell}$  (discharging quantity),  $p_{min}$  (min price),  $p_{max}$  (max price), Profit
2: Initialise constants:  $R$  (ramp rate),  $B_c$  (battery capacity),  $C_{min}$  (min charge level)
3: Charging/Discharging Bottlenecks
4: if Period of  $p_{min} <$  Period of  $p_{max}$  then
5:   Charging Strategy:
6:    $x_{buy} \leftarrow \min(B_c - c, R)$  ▷ Charging Bottleneck
7:    $c \leftarrow c + x_{buy}$ 
8:    $x_{sell} \leftarrow \min(c - C_{min}, R)$  ▷ Discharging Bottleneck
9:    $c \leftarrow c - x_{sell}$ 
10:  Profit  $\leftarrow (p_{max} \times x_{sell} \times \mathcal{E}_d) - (\frac{p_{min} \times x_{buy}}{\mathcal{E}_c})$ 
11: else
12:  Discharging Strategy:
13:   $x_{sell} \leftarrow \min(c - C_{min}, R)$  ▷ Discharging Bottleneck
14:   $c \leftarrow c - x_{sell}$ 
15:   $x_{buy} \leftarrow \min(B_c - c, R)$  ▷ Charging Bottleneck
16:   $c \leftarrow c + x_{buy}$ 
17:  Profit  $\leftarrow (p_{max} \times x_{sell} \times \mathcal{E}_d) - (\frac{p_{min} \times x_{buy}}{\mathcal{E}_c})$ 

```

Algorithm 1. TS3 Bottleneck.

By adaptively modulating charging and discharging schedules based on the sequence of minimum and maximum price periods, the proposed strategy effectively mitigates the impact of bottleneck constraints, thereby increasing trading frequency and maximizing overall profits.

TS3-Dual: Dual markets

Our dual-market strategy, TS3-Dual, simultaneously optimizes trading decisions across both the DAM and BM, ensuring effective coordination between the two markets. This approach exploits the differing temporal resolutions and decision lead times, specifically:

- DAM positions are fixed at time t for the delivery window spanning $t + 12$ to $t + 36$, using hourly granularity over 24 hours.
- BM positions, by contrast, are determined at time $t + 12$ —12 hours after the DAM commitments have been locked in. These BM positions rely on an 8-hour-ahead forecast extending to $t + 20$, with half-hourly granularity.

The core focus of TS3-Dual is to capture midday arbitrage opportunities within the DAM, while allocating the remaining periods before and after the DAM trades to the BM to take advantage of the BM's persistent price volatility.

To implement this coordination, we segment the price data into subsets optimized for trading in each market, structured as follows:

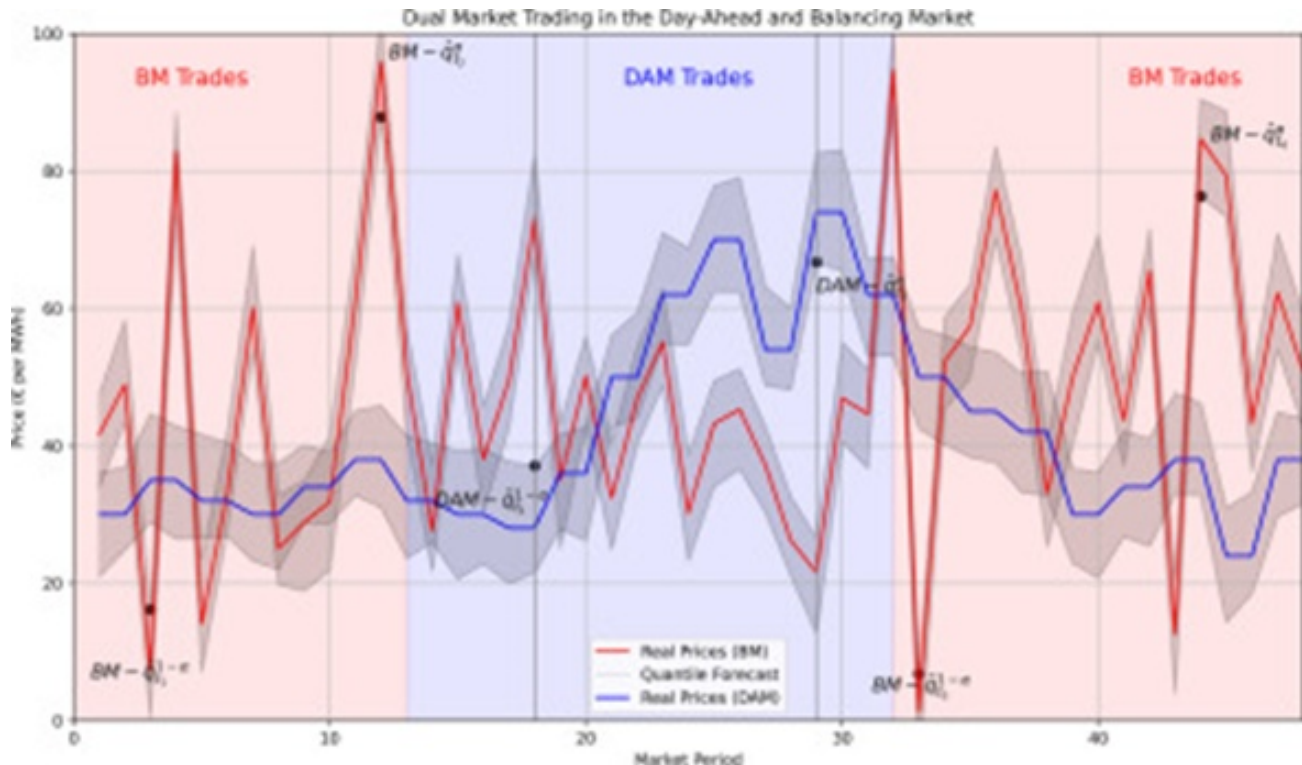


Figure 5. TS3-dual strategy.

- Early-Bidding in the BM (PS1): Designed specifically for BM activity, PS1 covers time intervals that occur before any DAM trades. This segment enables proactive positioning and early bidding to enhance BM trading outcomes.
- DAM Trades - PS2: Reserved exclusively for DAM operations, this subset spans the interval from the minimum-price period to the maximum-price period of the selected DAM trade pair.
- Late-Bidding in the BM - PS3: Analogous to PS1, PS3 is allocated to BM trades but targets periods following the completion of DAM trades. It is positioned to support subsequent bidding opportunities in the BM.

Within each subset, we apply the same procedural logic as outlined for TS3, iteratively processing all subsets until no further viable buy–sell pairs remain. By partitioning the price timeline in this manner, TS3-Dual effectively distributes and synchronizes trading activity across both the DAM and BM, as illustrated in **Figure 5**.

Additionally, we implemented the same three trading strategies (TS1, TS2, and TS3) using a more sophisticated Mixed-Integer Linear Programming (MILP) formulation [47] in place of the heuristic methods described above. The complete code for all trading strategies and associated algorithms is available at GitHub.

Experimental Results

This section presents the findings of our investigation, emphasizing the real-world utility of quantile forecasts for Battery Energy Storage System (BESS) trading in the Day-Ahead Market (DAM) and Balancing Market (BM). We assess three separate trading strategies—TS1, TS2, and TS3—each integrating quantile-based predictions with realistic operational constraints to maximize efficiency. The following subsections provide an in-depth examination of these strategies, covering the selection of quantile pairs, choice of forecasting models, overall forecast quality, and the principal differences between the DAM and BM that shape trading performance. In addition, we perform a comprehensive economic evaluation of BESS, illustrating the financial consequences of applying these strategies across both markets.

Trading strategies

Our assessment of TS1, TS2, and TS3 employs a notional battery characterized by a capacity of 1 MWh, discharge efficiency (ε_d) of 80%, and charge efficiency (ε_c) of 98%. Each strategy is evaluated over the timeframe from mid-2019 to mid-2022, encompassing both the Irish DAM and BM. To avoid executing loss-making trades, every strategy incorporates a minimum expected profit threshold. A trade is only carried out if the anticipated profit, computed as

$\varepsilon_d \cdot \hat{q}_{t_2}^a - \frac{\hat{q}_{t_1}^{1-a}}{\varepsilon_c}$, is at least zero. This filter proves especially important in the BM, where greater price volatility and

unpredictable price movements heighten the likelihood of unprofitable outcomes. Moreover, TS2, TS3, and TS3-Dual limit daily trading to a maximum of 3 trades, provided each satisfies the expected profit criterion. This cap is intended to discourage excessive trading during periods of slim margins, thereby improving trade selectivity and promoting steadier profitability in both markets.

Among the strategies, TS3 consistently delivers the strongest performance in both the DAM and the BM, as shown in **Figure 6**, outperforming TS1 and TS2 in total profit. This superiority stems from TS3's flexibility in ordering buy and sell timestamps, which allows more trades than TS2—a factor critical to profit maximization when relying on quantile forecasts. The removal of sequential timestamp restrictions enables TS3 to exploit price swings better and handle battery state-of-charge limitations than TS1 or TS2. Although the BM carries a higher risk of trades failing to meet the expected profit threshold due to its volatility, TS3 achieves a more pronounced profit uplift relative to TS1 and TS2, thanks to the BM's half-hourly settlement intervals, which provide substantially more trading windows than the hourly structure of the DAM. By dynamically adjusting buy/sell pairs based on quantile predictions while respecting battery constraints, TS3 navigates the BM's variable conditions more effectively.

The introduction of TS3-Dual, which coordinates trading across both the DAM and BM, further highlights the benefits of market diversification in energy arbitrage. By partitioning the trading horizon between the two markets, this dual approach reduces exposure to risks specific to any single market. It takes particular advantage of the BM's frequent intraday price movements to uncover additional profitable opportunities beyond those available in the DAM alone. **Table 2** summarizes the financial performance of TS3 across different quantile pairs and markets over the analyzed year. These outcomes illustrate how each strategy compares against key benchmarks, including perfect foresight (PF) as the theoretical upper limit on achievable profit and the baseline quantile pair (0.5–0.5).

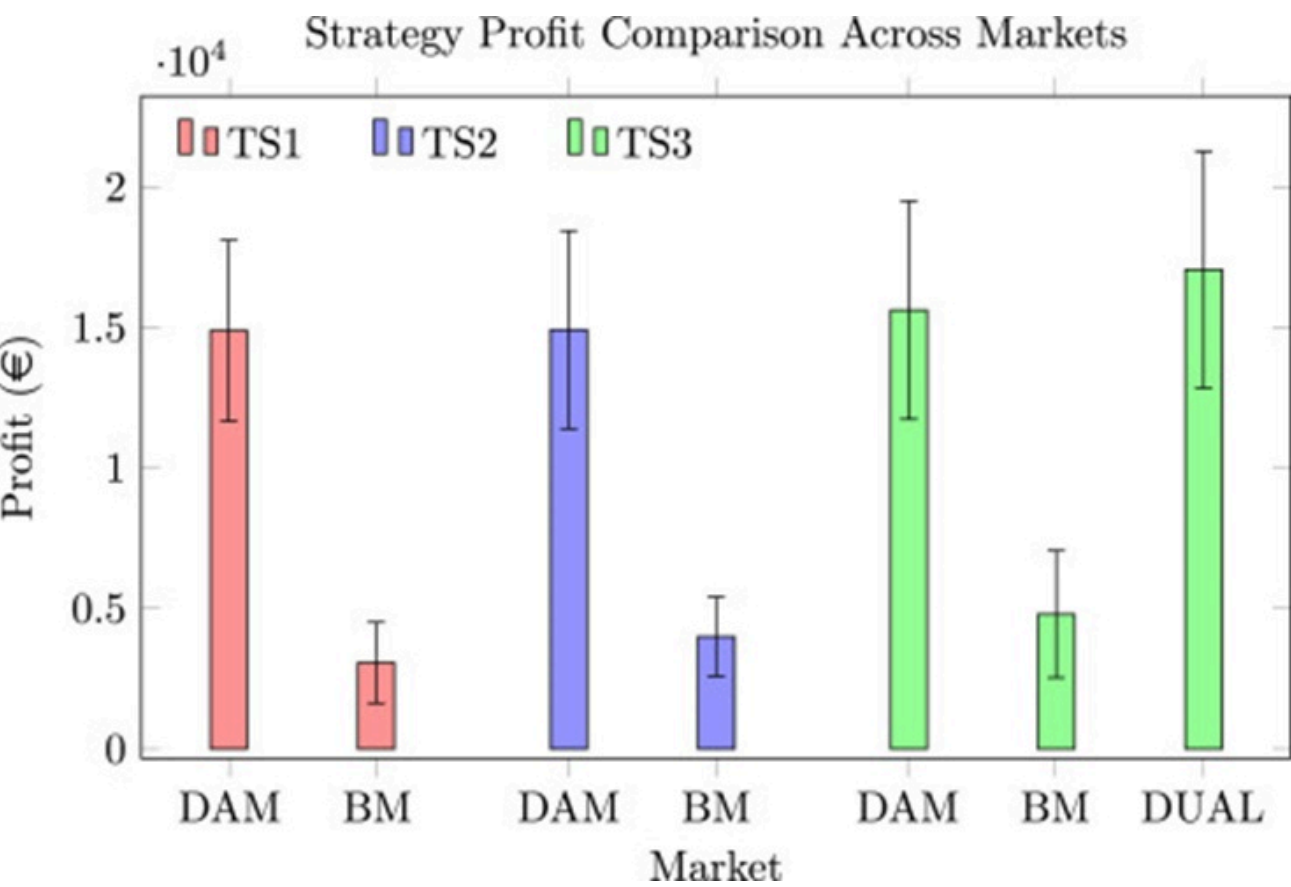


Figure 6. Average profit for TS1, TS2, and TS3 in each market. Error bars indicate the range observed across different quantile pairs.

Trading in the day-ahead market

Among the evaluated trading strategies, all generate higher profits in the DAM compared to the BM, with TS3 reliably surpassing TS1 and TS2, as depicted in [Figure 6](#). Detailed examination of TS3 performance in the DAM ([Table 2](#)) indicates that the baseline quantile pair 0.5–0.5 delivers the highest or near-highest returns across the full set of models. For KNN and LGBM, the 0.5–0.5 pair clearly outperforms alternative quantile combinations, whereas for RF and DNN, it comes very close to the best-performing pairs. Overall, this quantile configuration yields the highest average profit of €17,011 across all models, capturing approximately 60% of the theoretical maximum profit achievable under perfect foresight (€28,212).

The comparatively modest error rates observed in the DAM reduce the influence of quantile pair selection on overall profitability, implying that volatility considerations play a less decisive role than in the BM, where quantile choice exerts a stronger impact. From a practical standpoint, this suggests that DAM participants may derive greater benefit from prioritizing operational efficiency and straightforward strategies over intricate quantile-based refinements, given the limited incremental gains available in this more predictable market setting.

Table 2. Financial profits from TS3: bottleneck-controlled strategy.

Market	Model	Quantiles □□	0.5–0.5	0.1–0.3	0.3–0.5	0.5–0.7	0.7–0.9	0.3–0.7	0.1–0.9	PF	Model Average
DAM	KNN	€14,764	€12,570	€14,135	€13,557	€13,524	€13,036	€7,618	€28,212	€9,844	

	RF	€18,722	€18,503	€18,838	€17,434	€16,916	€17,520	€15,015	€28,212	€17,564	
	LGBM	€19,420	€16,446	€19,272	€18,032	€17,160	€18,178	€14,263	€28,212	€17,539	
	DNN	€15,137	€14,593	€15,740	€14,914	€15,337	€15,196	€11,585	€28,212	€14,643	
BM	KNN	€4,358	€1,047	€926	€788	€1,414	€69	€0	€71,669	€1,229	
	RF	€7,860	€5,301	€7,955	€8,697	€8,741	€5,063	€0	€71,669	€6,231	
	LGBM	€6,109	€4,408	€6,416	€9,391	€9,713	€5,630	€42	€71,669	€5,958	
	DNN	€5,685	€4,898	€6,747	€8,988	€8,339	€5,664	€51	€71,669	€5,767	
DUAL	KNN	€16,070	€12,883	€14,411	€13,792	€13,947	€13,055	€7,617	€82,683	€13,111	
	RF	€21,079	€20,091	€21,223	€20,042	€19,537	€19,038	€15,014	€82,683	€19,432	
	LGBM	€21,250	€17,766	€21,195	€20,848	€20,072	€19,866	€14,275	€82,683	€19,325	
	DNN	€16,841	€16,061	€17,762	€17,609	€17,837	€16,894	€11,599	€82,683	€16,372	
DAM Average			€17,011	€15,528	€16,996	€15,984	€15,734	€15,983	€12,120	€28,212	€15,622
BM Average			€6,003	€3,913	€5,511	€6,966	€7,052	€4,107	€23	€71,669	€4,797
DUAL Average			€18,810	€16,700	€18,648	€18,073	€17,848	€17,213	€12,126	€82,683	€17,060

Trading in the balancing market

Unlike the DAM, the BM shows greater responsiveness to quantile-based forecasting approaches owing to its pronounced volatility and greater forecasting difficulty. As presented in [Table 2](#) for TS3, the baseline 0.5–0.5 quantile pair generates an average profit of €6003, equivalent to roughly 8% of the perfect-foresight benchmark of €71,669. However, wider quantile pairs such as 0.7–0.9 and 0.5–0.7 outperform this reference pair. In particular, the 0.7–0.9 quantile combination achieves the highest average profit of €7052 (approximately 9.8%), while the 0.5–0.7 pair follows closely with €6966 (about 9.7%). The 0.7–0.9 pair proves most effective for RF and LGBM, whereas KNN achieves its strongest results with the 0.5–0.5 pair, and DNN performs best using 0.5–0.7. This trend indicates that broader quantile spans are often better suited to capturing the extreme price movements characteristic of the BM. However, outcomes for TS3 vary considerably across quantile pairs and remain strongly model-dependent, as highlighted in [Figure 7](#).

While the BM consistently delivers lower profitability than the DAM and the perfect-foresight (PF) benchmark—with the strongest outcome reaching only about 9.8% of the potential €71,669 achievable under PF—this gap reflects the considerable forecasting difficulties and the inherent unpredictability of the BM. Nonetheless, it also demonstrates the meaningful, albeit demanding, profit opportunities available to participants capable of producing accurate forecasts in such a volatile setting. The frequent, sharp price movements characteristic of the BM create distinctive arbitrage opportunities; through sophisticated modeling and well-chosen quantile selections, traders can effectively exploit these swings. Achieving consistent success, however, requires high precision and flexibility, since even minor inaccuracies in forecasts can substantially erode returns.

Trading dual market positions

In the dual-market framework, TS3-Dual effectively combines the relative stability of the DAM with the high-volatility environment of the BM, coordinating positions across both markets to optimize overall returns. As shown in [Table 2](#), the baseline 0.5–0.5 quantile pair delivers consistently strong performance, generating an average profit of €18,810 and

capturing 22.7% of the theoretical maximum profit of €82,683 under PF. The 0.3–0.5 quantile pair performs nearly as well, with an average of €18,648, equivalent to 22.5% of the profit potential. These results illustrate TS3-Dual's ability to efficiently utilize simple quantile configurations, even under differing conditions between the DAM and BM.

The LGBM model stands out as the leading performer in TS3-Dual, achieving a profit of €21,250 with the 0.5–0.5 quantile pair—corresponding to 25.7% of the PF benchmark. Although the DAM alone captures a higher percentage of its own profit potential (60%), its absolute profit remains lower than that obtained through the dual-market approach. This underscores the advantage of integrating the DAM's predictability with the BM's greater upside potential, yielding a superior overall financial outcome. While the BM in isolation produces the lowest returns and the smallest share of profit potential (9.8%), incorporating it into the dual strategy elevates total profits beyond what either market can achieve on its own. These findings affirm the economic merit of dual-market participation, with TS3-Dual systematically outperforming single-market strategies across all quantile pairs evaluated (Figure 6).

Performance of non-conventional quantile pairs

Examination of non-conventional quantile pairs (e.g., 0.3–0.5, 0.5–0.7, 0.7–0.9) in the DAM, BM, and dual-market strategies reveals greater diversity in profit outcomes compared to conventional pairs (e.g., 0.5–0.5, 0.3–0.7, 0.1–0.9); see Figure 7. In the DAM, non-conventional pairs exhibit a relatively steady profit profile, with combinations such as 0.3–0.5 and 0.5–0.7 delivering profitability and consistency levels comparable to those of conventional pairs. Moreover, the narrower error bars associated with DAM profits indicate that non-conventional pairs provide greater stability and reduced sensitivity to differences across forecasting models, making them more robust to model-specific variations or prediction inconsistencies.

By contrast, the BM displays lower average profits alongside markedly higher variability, affecting both conventional and non-conventional pairs alike. Among non-conventional options, pairs such as 0.5–0.7 and 0.7–0.9 yield modestly higher returns than their conventional counterparts, though the wide error bars reflect considerable model-dependent uncertainty. In the dual-market strategy, the baseline 0.5–0.5 pair produces the highest profits overall, yet non-conventional pairs—particularly 0.3–0.5 and 0.5–0.7—also deliver reliable performance with moderate variability. While certain pairs exhibit a general trade-off between higher profits and increased variance, these unconventional configurations prove effective at capturing price swings and balancing risk, rendering them especially well-suited for dual-market applications.

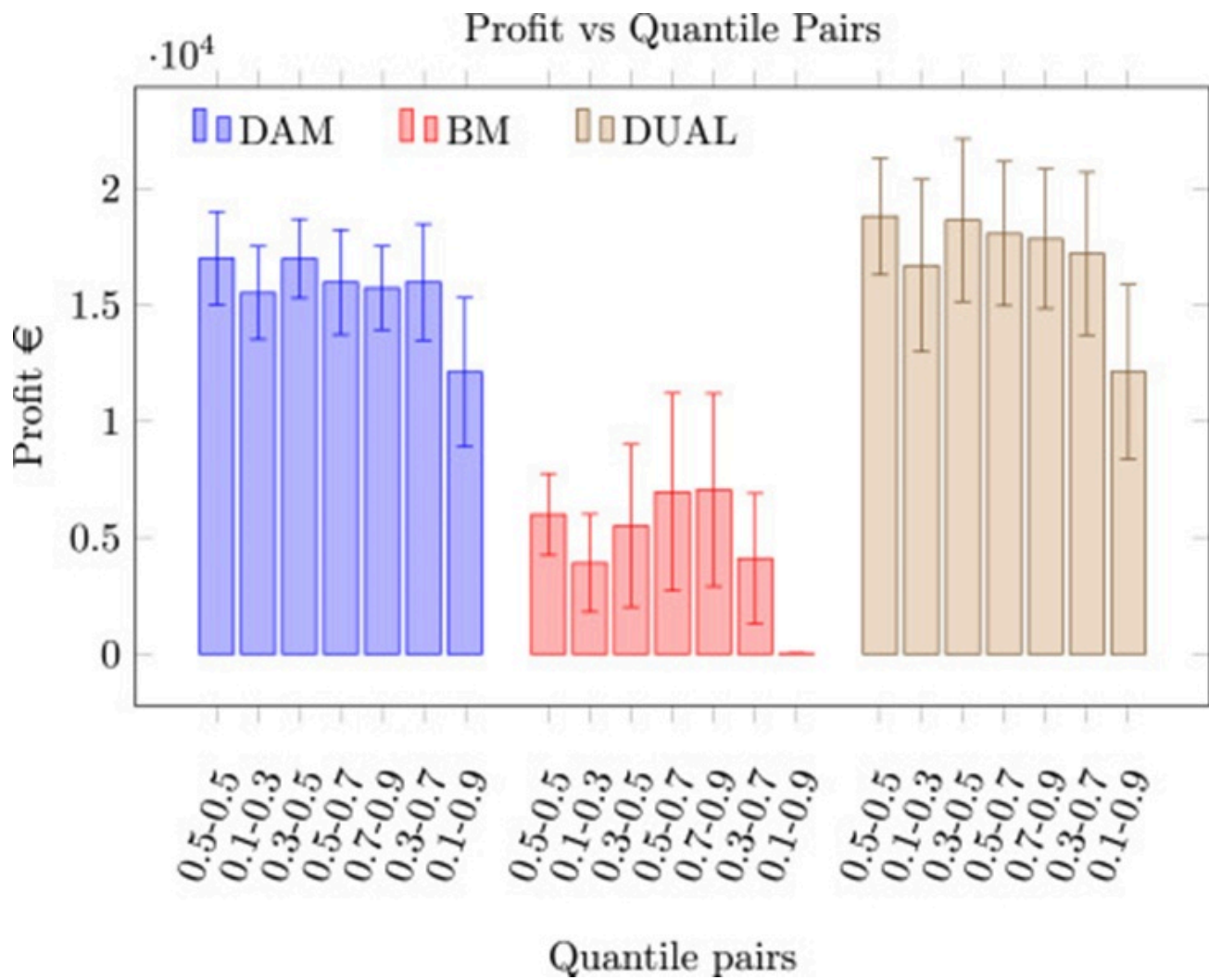


Figure 7. TS3 profit for DAM, BM, and DUAL quantile pairs. Error bars reflect variability across different forecasting models.

Model selection and forecast accuracy

This section emphasizes the critical role of evaluating model performance, forecast precision, and model choice in maximizing profitability across diverse energy market settings. **Figure 8** displays the profit outcomes for the various models (KNN, DNN, LGBM, and RF) under TS3 in the DAM, BM, and DUAL market strategies. In the DAM, both RF and LGBM deliver the highest profits, with moderate variability, reflecting consistent and reliable performance across the chosen quantile pairs. The BM exhibits markedly lower profits across models, along with considerable variability, indicating strong dependence on quantile-pair selection and a generally less predictable operating environment. For the DUAL approach, RF and LGBM again demonstrate strong results, with error bars narrower than those in the BM but wider than in the DAM, illustrating a compromise between high profitability and sensitivity to quantile configuration. Collectively, these observations indicate that RF and LGBM are the most suitable models for achieving stable, robust performance in the DAM, BM, and DUAL framework.

Figure 9 shows the relationship between model accuracy, as quantified by the pinball score, and realized profit under TS3 across the DAM, BM, and DUAL strategies. For TS3 in the DAM and for TS3-DUAL, a clear inverse correlation emerges: lower pinball errors are strongly associated with higher profits, highlighting the decisive influence of accurate forecasting. In contrast, the BM shows a notably weaker link between forecast accuracy and profit among the leading

models; reduced accuracy does not consistently translate into lower profits, suggesting that factors beyond mere predictive precision significantly affect profitability in this market. These patterns reinforce the essential role of forecast accuracy in profitability across the DAM, BM, and DUAL approaches, underscoring the importance of selecting models that deliver superior predictive performance.

Table 3 summarizes the performance of quantile regression (QR) models in the DAM and BM based on the Aggregate Pinball Score (APS). LGBM consistently records the lowest APS values across both markets (3.62 in the DAM and 12.48 in the BM), confirming its superior ability to capture price uncertainty under different market dynamics. RF follows closely behind LGBM, while KNN registers the highest APS in both markets, revealing its comparative weakness in addressing the complexity and volatility inherent in electricity price behavior—especially pronounced in the BM. The substantially higher average APS in the BM (13.10) relative to the DAM (4.66) further illustrates the elevated forecasting difficulties encountered in the balancing environment.

Table 3. APS results for QR in the DAM and BM.

Model	APS (DAM)	APS (BM)
KNN	6.65	14.09
LGBM	3.62	12.48
RF	3.63	12.66
DNN	4.73	13.16
Avg.	4.66	13.10

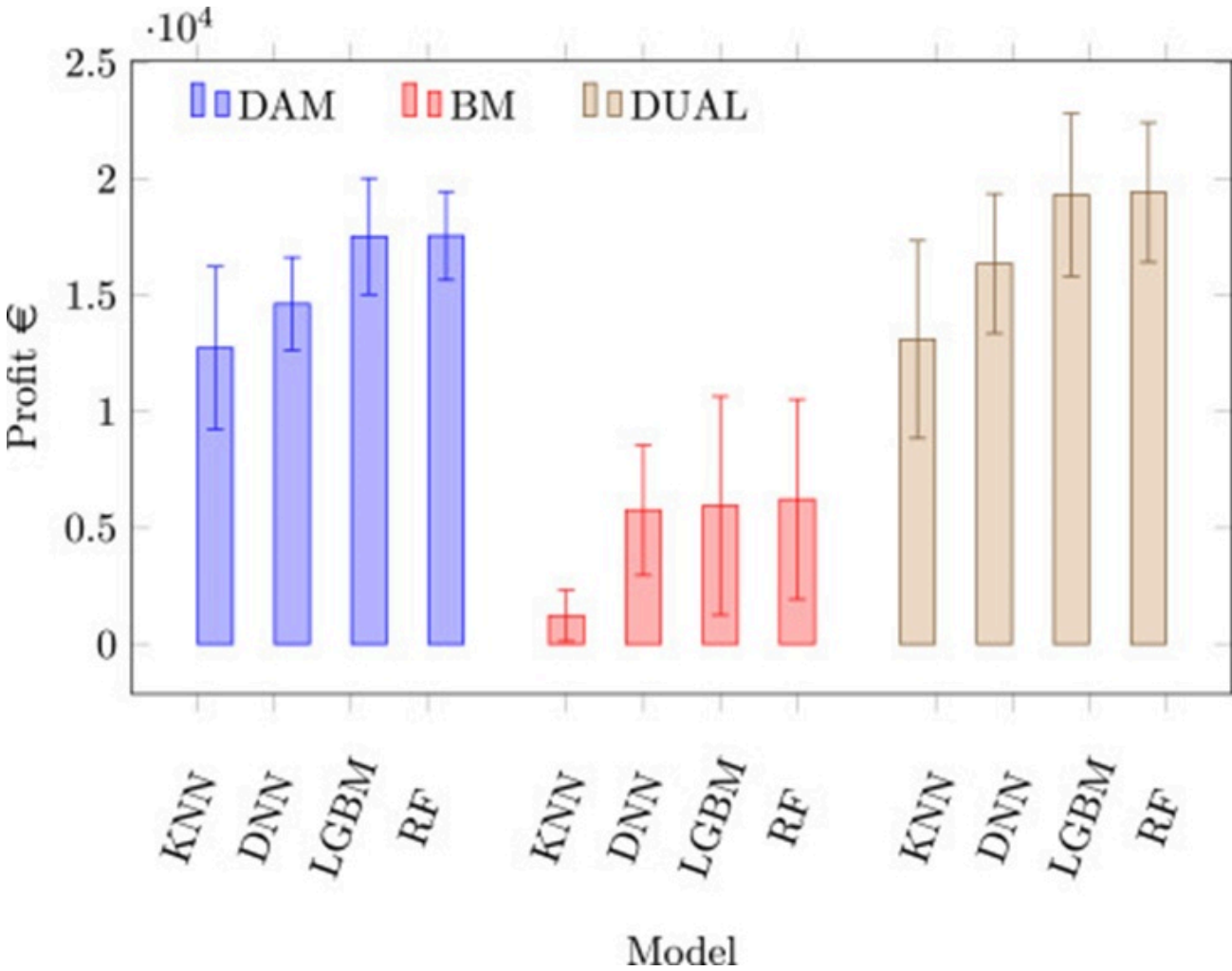


Figure 8. TS3 profit for models in the DAM, BM & Dual with range in quantile pair.

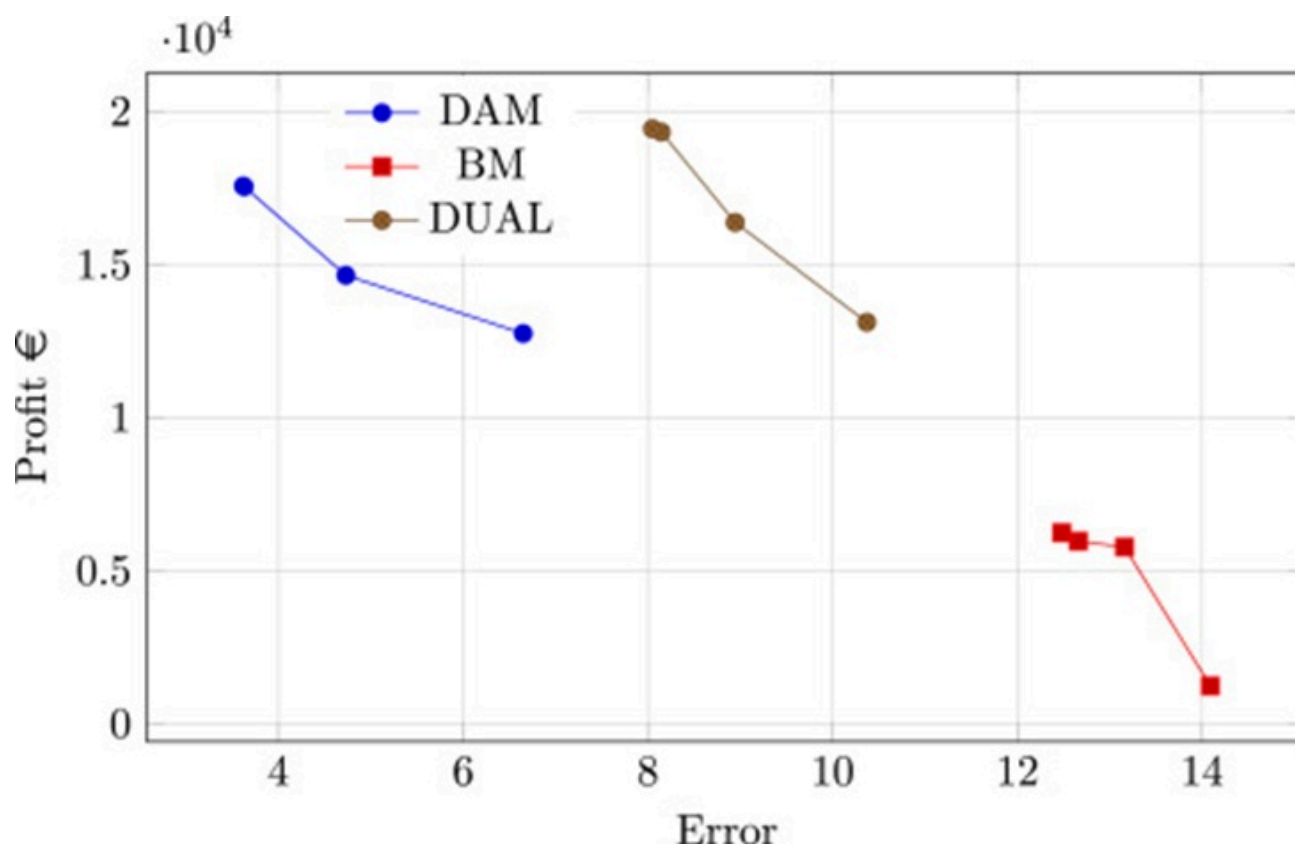


Figure 9. TS3 Aggregate Pinball Score of Model vs Profit.

Improved dual-market strategies

This research addresses key shortcomings in current dual-market trading approaches by incorporating realistic forecasting horizons and operational constraints, thereby closing gaps that are often neglected in earlier studies. Conventional methods, such as those of Krishnamurthy *et al.* [40], Brijs *et al.* [52], and Gomes *et al.* [53], commonly rely on unrealistically extended forecasting horizons for the BM, which prove unfeasible under real-world conditions characterized by high volatility [30, 31, 48]. In contrast, our framework synchronizes BM trading decisions with DAM strategies by leveraging real-time forecasting and constraints that mirror actual market behavior. This methodology not only improves forecast reliability and trading performance but also validates the feasibility of integrated dual-market participation using authentic datasets. Moreover, although heuristic techniques paired with machine learning models enhance flexibility in rapidly changing markets [34], they generally lack the formal guarantees provided by exact optimization methods. They may deliver suboptimal results in strictly regulated settings [43]. By combining quantile regression (QR) with hybrid optimization techniques, our work establishes a strong balance between adaptability and reliability, yielding trading strategies for the DAM and BM that are both highly effective and practically implementable.

Economic viability - scenario analysis

This section offers a thorough evaluation of the economic feasibility of various BESS configurations, examining the principal factors that affect their financial returns and operational effectiveness. Our analysis includes scenario modeling that accounts for critical variables, including capital expenditures, ongoing maintenance requirements, degradation-induced costs, efficiency-related losses, and evolving market conditions. The primary objective is to assess the long-term profitability and economic prospects of different BESS units over an anticipated operational life of 10–15 years. In the discussion that follows, as elaborated by Baxter and Byrne [49] and Herzer [50], we examine the main elements influencing the revenue streams generated by BESS operations. These factors include:

- CAPEX: Upfront costs for battery acquisition, encompassing auxiliary systems, installation, commissioning, permitting, and civil engineering works.
- Fixed O&M (€/kW-year): Fixed maintenance expenses along with variable costs incurred over the system's lifetime, determined by operational hours or cycle counts. Maintenance costs for all modeled batteries are assumed to rise by 2% annually, consistent with findings from the Sandia report [54].
- Degradation-related costs: Expenditures arising from capacity fade due to cycling, which may necessitate the addition or replacement of cells, resulting in progressive reductions in available capacity and overall efficiency. Degradation is modeled at an annual rate of 1.55%, aligned with lithium-ion battery performance data reported by Gräf et al. [35].
- Efficiency costs: Expenses associated with round-trip efficiency losses (€/kWh). All battery configurations are modeled with a uniform 95% efficiency for both charging and discharging processes.
- Depth of Discharge: The proportion of rated capacity that is discharged during operation, expressed as a percentage.
- Ramp Rate: Expressed as the ratio between rated energy and rated power (e.g., 2-hour Tesla Megapack or 1-hour lithium-ion battery, per Baxter [54]).
- Calendar Life (years): The longest feasible service life, governed by aspects like average state of charge; lithium-ion batteries, for example, typically reach end-of-life once capacity drops below 60% of nominal value. Every battery examined here is modeled to have a service life of 10 to 15 years.
- Market registration costs associated with participating in the I-SEM DAM and BM total €18,294 annually. This figure comprises a one-time registration charge, recurring annual membership fees, a BM entry fee, a BM participation fee, plus per-MWh transaction charges. A full itemized list appears in SEMO [55] for I-SEM DAM & IDM and in SEMO [56] for the BM.

The following items are deliberately excluded owing to difficulties in obtaining dependable figures:

- Warranty (€/kWh-year): Yearly payments linked to performance guarantees.
- Insurance (€/kWh): Coverage premiums protecting against unexpected hazards.
- End-of-life costs: Outlays for dismantling, shipping to recycling centers, and responsible disposal of lithium-ion modules.
- Subsidies and government incentives: Available grants, tax credits, or other public support schemes that could reduce initial capital requirements; their presence, size, and eligibility differ widely.

Battery options

We evaluate several battery setups based on specifications drawn from the SEM Committee [57]. These include compact units rated at 3 MWh (Scottish Power, Battery A) and 3.9 MWh (Tesla Megapack, Battery B), as well as larger-scale systems rated at 10 MWh (Avolta Storage, Battery C) and 39 MWh (ten Tesla Megapacks, Battery D). Revenue projections for each configuration are generated using the best-performing dual-market strategy (TS3-Dual), customized to each battery's technical profile.

Smaller batteries: A & B

- Battery A – Scottish Power (3 MWh) — Features a 1-hour duration cycle, full discharge capability of 3 MWh, and round-trip charge/discharge efficiency of 95%. Capital expenditure stands at €1,671,000.00 (€557/kWh), while yearly maintenance is €11,000 (€4/kWh). This smaller footprint suits applications that need relatively brief discharge windows.

- Battery B – Tesla Megapack (3.9 MWh) — Built around a 2-hour cycle with charge/discharge efficiency and ramp characteristics comparable to Battery A. Acquisition cost is €1,722,628.98 (€447/kWh) and annual upkeep totals €7,730.96 (€2/kWh). The additional energy storage makes it especially appropriate for applications that require longer discharge intervals.
- Battery C – Avolta Storage (10 MWh) — Configured for a 1-hour cycle, capable of discharging up to 9 MWh, with 95% charge/discharge efficiency. The total build cost is €4,850,000 (€485/kWh), and yearly maintenance is €100,000 (€10/kWh). It offers a balanced solution for medium-to-large projects that demand high power over short periods.
- Battery D – 10 × Tesla Megapack (38.5 MWh) — Utility-scale arrangement with a 2-hour cycle, mirroring the efficiency and ramp behavior of Battery B. Thanks to a quantity discount applied to the ten-unit purchase, the capital cost is €13,726,186.17 (€356/kWh), and annual maintenance amounts to €61,593.89 (≈ €2/kWh). This design is ideal for high-volume storage applications and demonstrates the cost efficiencies attainable at larger scales.

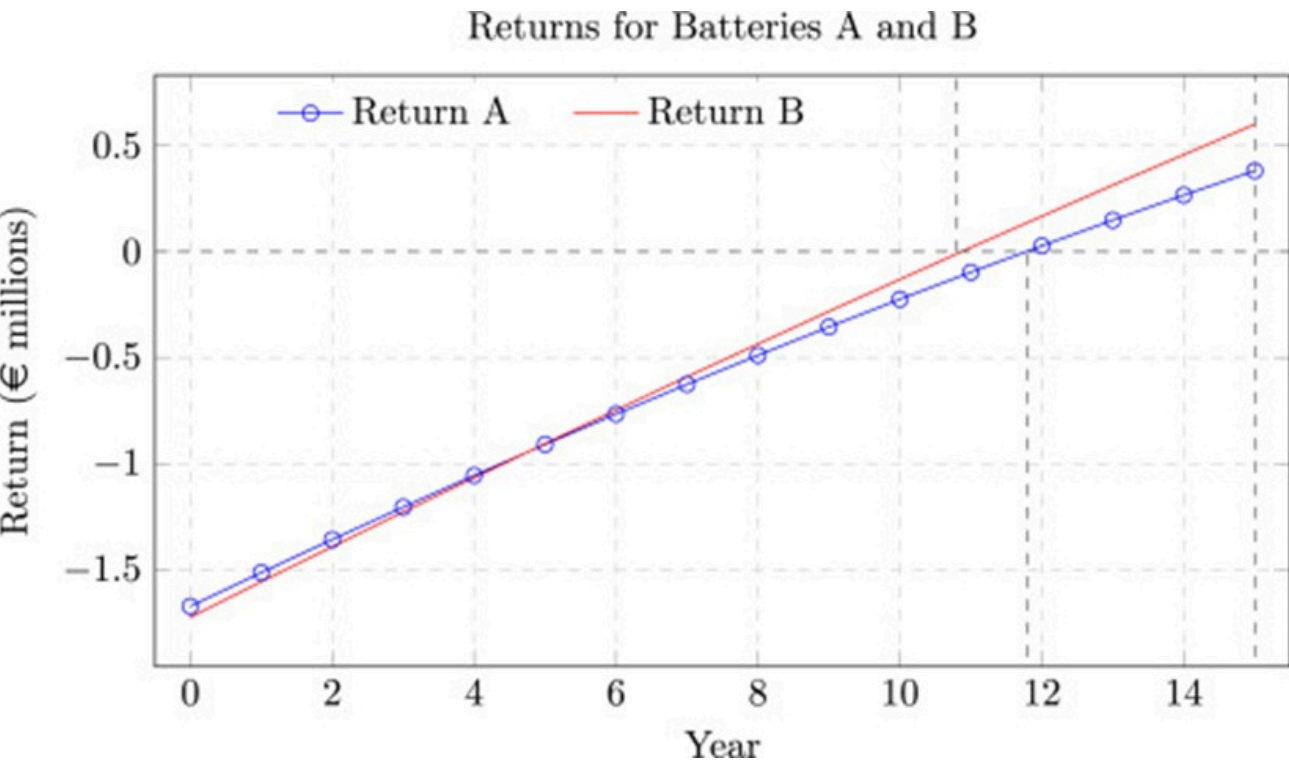


Figure 10. 15-year cost breakdown for the 3 MW Scottish Power and 3.9 MW Tesla capacity.

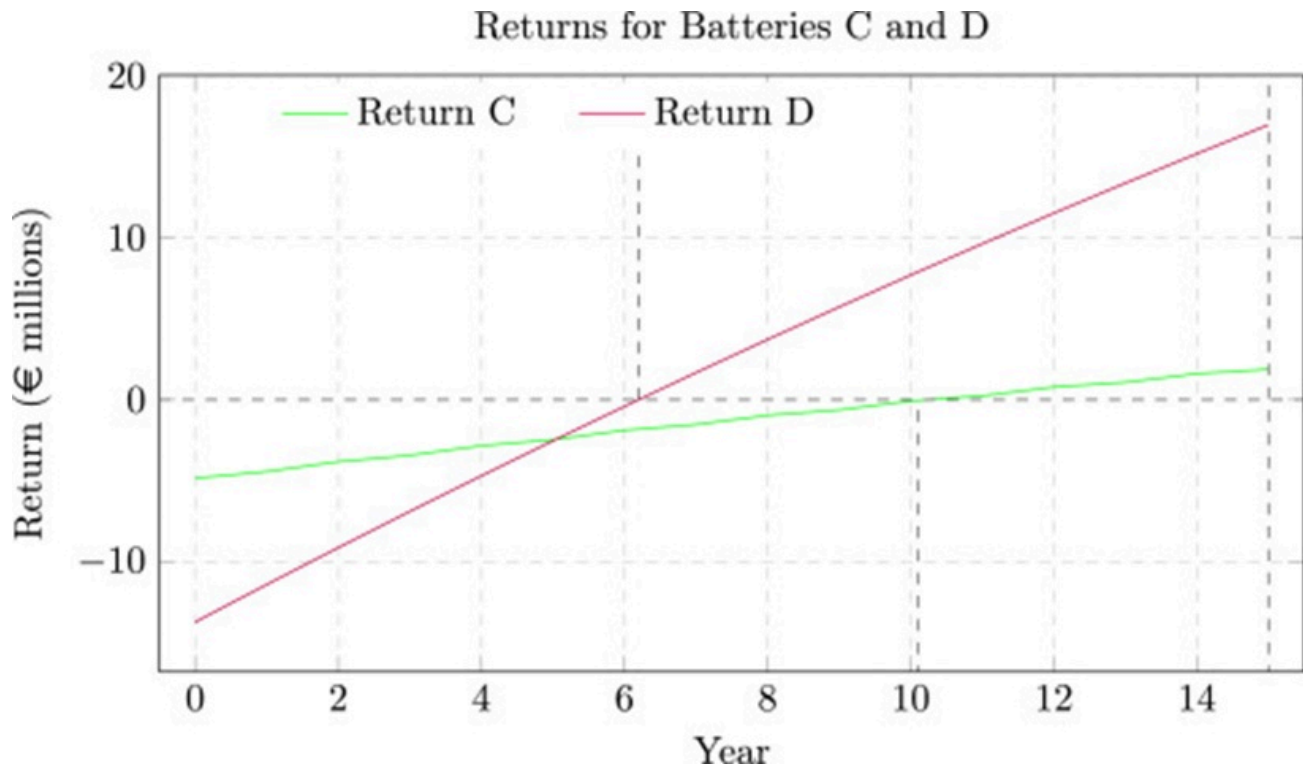


Figure 11. 15-year cost breakdown for Avolta Storage (C) and Tesla MegaPacks (D) totaling 38.5 MWh.

Economic viability of BESS units

This section evaluates the long-term financial attractiveness of different BESS configurations, with particular attention to the time required to reach breakeven and cumulative returns over a projected 10–15-year operating life. **Figure 10** depicts the 15-year return-on-investment trajectory for Batteries A and B. **Figure 11** compares the corresponding 15-year performance for Batteries C and D.

1. The 3 MW Scottish Power unit, with capital costs of €557/kW and annual maintenance of €11/kW, remains unprofitable until year 12 and ultimately delivers a 16% return by the end of year 15.
2. The 3.9 MW Tesla Megapack, featuring capital costs of €447/kW and annual maintenance of €2/kW, achieves breakeven in year 11 and generates a 34% return by year 15.
3. The 10 MW Avolta Storage unit, with capital costs of €485/kW and annual maintenance of €10/kW, becomes profitable by year 11 and attains a 38% return by year 15.
4. The 38.5 MW configuration (10 Tesla Megapacks), carrying capital costs of €356/kW and annual maintenance of €2/kW, reaches profitability as early as year 7, achieves a 56% return by year 10, and delivers a 123% return by year 15.

These outcomes clearly demonstrate how economies of scale and differences in upfront and ongoing cost structures strongly influence the overall economic prospects of BESS deployments.

The results reflect the ongoing maturation of battery storage technology and the decisive importance of continued cost declines. When factoring in the potential impact of financing costs on capital and maintenance expenditures, Batteries A and C appear less compelling as investment targets. In contrast, Batteries B and, particularly, Battery D stand out as economically robust options. Collectively, these findings illustrate recent progress in improving the cost-competitiveness of BESS while emphasizing the critical role of optimal sizing decisions. They also reveal the complex interrelationship

among initial capital outlays, recurring maintenance expenses, system scale, and sustained profitability—factors that will continue to shape advancements in energy storage deployment and its effective integration into power systems.

Limitations

The present analysis rests on several simplifying assumptions. Annual profits are assumed to remain constant based on historical trading performance, even though real markets are subject to considerable fluctuations and structural evolution over extended periods. Battery capacity fade is modeled at a fixed annual rate of 1.55% [35], without accounting for potentially faster degradation caused by intensive cycling, extreme temperature, or power conditions. Although capital expenditure, operations and maintenance costs, and round-trip efficiency losses are explicitly included, the model omits prospective future reductions in battery manufacturing costs or gains in storage round-trip efficiency. Market-related assumptions likewise presume unchanging energy price regimes and regulatory frameworks across the full 15-year horizon, disregarding possible effects from accelerated renewable integration, policy reforms, or shifting grid flexibility requirements. Trading strategy performance is derived exclusively from past data, which may not adequately represent emerging conditions such as heightened competition in balancing services or changes in market depth and liquidity.

Moreover, the evaluation does not consider simultaneous optimization of ancillary service participation or exploitation of novel revenue streams that could augment pure arbitrage returns. Broader macroeconomic influences—including inflation, exchange-rate movements, and geopolitical uncertainties—are likewise excluded. Finally, the analysis omits any contribution from government subsidies, tax credits, or policy support mechanisms, which frequently play a pivotal role in offsetting the substantial upfront costs of battery projects and improving overall viability. As discussed by Zakeri et al. [58], instruments such as self-consumption incentives and time-varying tariffs can significantly boost revenues by capitalizing on renewable generation patterns and demand-side flexibility. Likewise, targeted support for peak-reduction or frequency-control services, as outlined by Filho et al. [59], has the potential to markedly enhance financial returns and revenue stability—especially within liberalized electricity markets—by better aligning economic rewards with system reliability objectives (Table 4).

Table 4. Financial profits from TS3: bottleneck-controlled strategy with MILP.

Market	Model	Quantiles □□	0.5–0.5	0.1–0.3	0.3–0.5	0.5–0.7	0.7–0.9	0.3–0.7	0.1–0.9	PF	Model Average
DAM	KNN	€18,085	€14,122	€14,987	€14,403	€14,335	€13,623	€8,201	€29,869	€13,965	
	RF	€19,954	€19,393	€19,588	€18,974	€17,693	€17,844	€16,674	€29,869	€18,589	
	LGBM	€20,554	€18,385	€19,509	€18,748	€18,216	€18,697	€16,355	€29,869	€18,638	
	DNN	€16,133	€15,295	€16,366	€16,231	€16,041	€15,477	€12,865	€29,869	€15,487	
BM	KNN	€4,646	€1,097	€963	€858	€1,480	€69	€0	€75,879	€1,302	
	RF	€8,377	€5,557	€8,272	€9,466	€9,142	€5,157	€0	€75,879	€6,567	
	LGBM	€6,511	€4,620	€6,672	€10,221	€10,159	€5,735	€47	€75,879	€6,281	
	DNN	€6,059	€5,134	€7,016	€9,782	€8,722	€5,769	€57	€75,879	€6,077	
DUAL	KNN	€17,128	€13,503	€14,985	€15,010	€14,588	€13,296	€8,459	€87,540	€13,852	
	RF	€22,465	€21,058	€22,068	€21,812	€20,434	€19,389	€16,672	€87,540	€20,556	
	LGBM	€22,648	€18,622	€22,038	€22,690	€20,994	€20,233	€15,852	€87,540	€20,439	
	DNN	€17,949	€16,834	€18,469	€19,164	€18,656	€17,206	€12,881	€87,540	€17,308	

DAM Average			€18,682	€16,799	€17,613	€17,089	€16,571	€16,410	€13,524	€29,869	€16,670
BM Average			€6,398	€4,102	€5,731	€7,582	€7,376	€4,183	€26	€75,879	€5,057
DUAL Average			€20,048	€17,504	€19,390	€19,669	€18,668	€17,531	€13,466	€87,540	€18,039

Conclusion

This research investigated the effectiveness of quantile-driven trading strategies for maximizing the profitability of Battery Energy Storage Systems (BESS) in the Day-Ahead Market (DAM) and the Balancing Market (BM). By evaluating three distinct approaches—TS1, TS2, and TS3—and developing an integrated dual-market framework (TS3-Dual), we illustrated the clear benefits of participating simultaneously in both markets to boost overall returns. Among the tested methods, TS3-Dual emerged as the superior performer, capitalizing on flexible timestamp sequencing to harmonize the relatively stable pricing environment of the DAM with the highly volatile conditions of the BM, thereby enabling greater trading frequency and substantially improved financial outcomes.

Our results highlight the critical importance of carefully selecting quantile pairs: in the BM, wider spans such as 0.7–0.9 proved particularly valuable for capturing outlier price movements, while in the DAM, the conventional 0.5–0.5 pair consistently delivered the strongest performance, reflecting the market's more predictable behavior. Model selection also played a decisive role in profitability, with RF and LGBM standing out for their robustness, adaptability, and superior forecast quality across varying conditions.

From an economic perspective, the analysis of cost structures and operational parameters confirms that BESS can achieve meaningful profitability in electricity markets when paired with suitable battery capacities and well-designed trading approaches. Looking ahead, future studies could usefully extend this work by incorporating intraday market opportunities, examining the influence of trade volumes on BM price formation, and exploring reinforcement learning algorithms to refine further trading decisions (e.g., Shavandi and Khedmati [60]).

The encouraging outcomes of this study reinforce the value of quantile-based forecasting and coordinated dual-market participation in unlocking the full economic potential of BESS. Ongoing advancements and deeper investigations in these areas hold significant promise for strengthening the contribution of energy storage to a more flexible, resilient, and renewable-integrated power system.

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Conflict of interest

None

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None

Ethics statement

None

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