Energy and AI 20 (2025) 100476

Contents lists available at ScienceDirect

Energy and AI

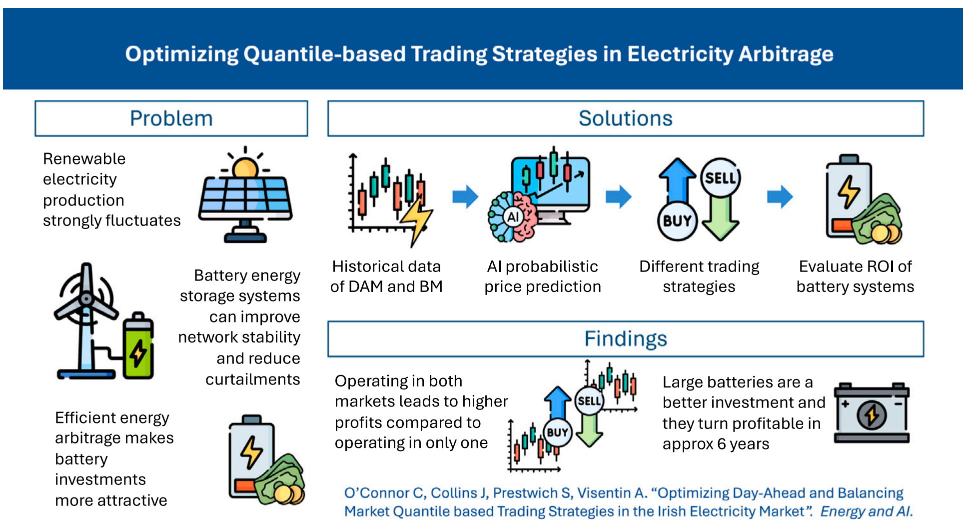
journal homepage: www.elsevier.com/locate/egyai

Optimising quantile-based trading strategies in electricity arbitrage

Ciaran O'Connor [a], Joseph Collins [b], Steven Prestwich [c], Andrea Visentin [c,*]

[a] SFI CRT in Artificial Intelligence, School of Computer Science & IT, University College Cork, Ireland
[b] School of Mathematical Sciences, University College Cork, Ireland
[c] SFI Insight Centre for Data Analytics, School of Computer Science & IT, University College Cork, Ireland

GRAPHICAL ABSTRACT



HIGHLIGHTS

- Proposing high-frequency quantile trading strategies for electricity markets.
- Transparent framework for quantile forecast generation and trading implementation.
- Simultaneous participation in Day-Ahead and Balancing Markets enhances profitability.
- Scenario analysis of battery storage systems operating in the electricity markets.

ARTICLE INFO

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

ABSTRACT

Efficiently integrating renewable resources into electricity markets is vital for addressing the challenges of matching real-time supply and demand while mitigating revenue losses caused by curtailments. To address this challenge effectively, the incorporation of storage devices can enhance the reliability and efficiency of the grid, improving market liquidity and reducing price volatility. In short-term electricity markets, participants face numerous options, each presenting unique challenges and opportunities, with trading strategies fundamental

* Corresponding author.
E-mail addresses: 119226305@umail.ucc.ie (C. O'Connor), 98718584@umail.ucc.ie (J. Collins), s.prestwich@cs.ucc.ie (S. Prestwich), andrea.visentin@ucc.ie (A. Visentin).

https://doi.org/10.1016/j.egyai.2025.100476
Received 23 June 2024; Received in revised form 2 January 2025; Accepted 20 January 2025
Available online 27 January 2025

towards maximising profits. This study explores the optimisation of day-ahead and balancing market trading in the Irish electricity market from 2019 to 2022, leveraging quantile-based forecasts. Employing three trading approaches with practical constraints, our research evaluates trading strategies, increases trading frequency, and employs flexible timestamp orders. Our findings underscore the profit potential of simultaneous participation in both day-ahead and balancing markets, especially with larger battery storage systems; despite increased costs and narrower profit margins associated with higher-volume trading, with the implementation of dynamic dual-market strategies playing a significant role in maximising profits and addressing market challenges. Finally, we evaluate the economic viability of four commercial battery storage systems through scenario analysis, showing that larger batteries achieve shorter returns on investment.

1. Introduction

The 21st century faces the challenge of incorporating variable renewable energy sources into our power systems. European electricity markets have experienced a remarkable surge in variable renewable generation, driven by policy incentives and renewable portfolio standards [1]. Over the past decade, global adoption of wind and solar power has steadily increased. Ireland has experienced a rapid expansion of the renewable generation share in its electricity mix, rising from 21.7% in 2014 to 39.5% in 2022 [2]. This widespread integration can introduce volatility in net power supply due to rapid and unforeseen changes in their output, potentially resulting in reliability concerns within the power system [3].

This widespread integration introduces volatility into electricity markets due to rapid and unforeseen changes in renewable output, which can lead to economic inefficiencies and challenges in balancing supply and demand [3]. Curtailments from surplus renewable generation during low-demand periods highlight these inefficiencies, resulting in lost revenue opportunities and imposing significant economic burdens on the market. In Ireland, curtailment rates, illustrated in Fig. 1, range between 3.0% and 5.9%, indicating that striving for increased capacity can be counterproductive, imposing significant economic burdens. In a recent study, Ireland had the highest curtailment percentage amongst the countries analysed [4], leading to an increase in studies aimed at facilitating renewables integration.

To address these challenges, modern electricity markets are increasingly leveraging Battery Energy Storage Systems (BESS) as a critical tool for mitigating supply and demand volatility caused by fluctuations in renewable energy output. BESS provides a practical solution to reduce these limitations by optimising the efficient utilisation of renewable energy and minimising curtailment losses. Strategic deployment of BESS not only alleviates network constraints but also enhances the economic value of renewable resources and improves grid reliability. Furthermore, the economic costs associated with curtailment, particularly the revenue losses caused by inadequate demand, highlight the pressing need for effective energy storage solutions. Addressing these challenges through market-driven approaches fosters a more resilient and efficient energy system, paving the way for greater integration of variable renewable energy sources.

The rising deployment of BESS underscores the increasing emphasis on energy arbitrage revenues [6]. BESS enables efficient energy redistribution, exploiting price differentials between low-demand and high-demand periods, thus reducing reliance on costly, fast-responding generation units like thermal peaker plants. Additionally, BESS contributes to load shifting, improved power quality, and grid stability. BESS has seen increasing integration in the Single Electricity Market (I-SEM), which includes the spot markets, the Day-Ahead Market (DAM) and the Balancing Market (BM). The DAM facilitates energy trading for next-day delivery through daily auctions, while the BM serves as the "market of last resort", addressing real-time deviations between supply and demand. Unlike the DAM, the BM operates at a much finer granularity, requiring near-instantaneous responses to system imbalances caused by demand variability, unforeseen generator outages, and the intermittent nature of renewable generation [7,8]. This is particularly challenging in Ireland, where wind energy, a dominant renewable resource, introduces significant volatility due to its unpredictable output [9]. The Irish BM relies heavily on the flagging and tagging process, a unique mechanism that ensures only energy-related balancing actions influence imbalance prices, filtering out distortions from system security measures [10]. These processes allow the BM to provide accurate price signals while maintaining grid stability.

Compared to other European BMs, such as the German and Iberian markets, the Irish BM operates within a smaller, more isolated grid, amplifying the impact of forecasting errors and renewable intermittency. In Germany, for instance, the BM benefits from greater grid interconnections and extensive cross-border cooperation, which help mitigate imbalances through shared resources [11]. Similarly, the Iberian BM incorporates a coordinated approach to renewable integration, leveraging its diverse energy mix and regional market structure. By contrast, the Irish BM's design must address its grid constraints and high renewable penetration with more localised balancing mechanisms. As renewable generation continues to expand, accurate real-time forecasting of supply–demand imbalances becomes increasingly critical for the Irish market, especially for enabling efficient BESS arbitrage and ensuring market resilience under volatile conditions [7,12]. Effective BESS arbitrage in these markets hinges on accurate probabilistic electricity price forecasting (PEPF), enhancing profitability and risk mitigation [13].

1.1. Contributions

In this paper, we respond to recent shifts in research trends that go beyond the traditional focus on PEPF metrics, which prioritise reliability, sharpness, and resolution to include trading strategies to better benchmark the forecasts. Our study delves into trading in the DAM & BM through probabilistic forecasting, making contributions to addressing gaps in the existing literature; namely:

- We introduce a comprehensive trading approach that incorporates practical BESS constraints, including battery capacity, ramp rates, energy efficiency, buy–sell order restrictions, and state-of-charge thresholds, to evaluate the usefulness of PEPF in both markets. Additionally, we provide a flexible Python implementation to support scenario analysis and assess the impact of these constraints on profitability, bridging theoretical models with practical market applications.
- We reduce entry barriers for researchers by making datasets for the DAM and BM publicly available. These datasets facilitate the testing of models and trading strategies, encouraging broader participation in EPF research, with a particular emphasis on the under-explored BM. They also support advanced applications such as transfer learning. Further details and access to the datasets are available at GitHub.[1]
- Our study advances trading strategies with a unique dual-market perspective, employing a real-time forecasting approach that simultaneously focuses on both the DAM and BM. Unlike previous studies, which often overlook realistic BM forecasting horizons, we align DAM decisions with BM positions using more realistic 8-h BM forecasts, ensuring practical and actionable trading strategies that optimise profitability.

[1] https://github.com/ciaranoc123/Balance-Market-Forecast

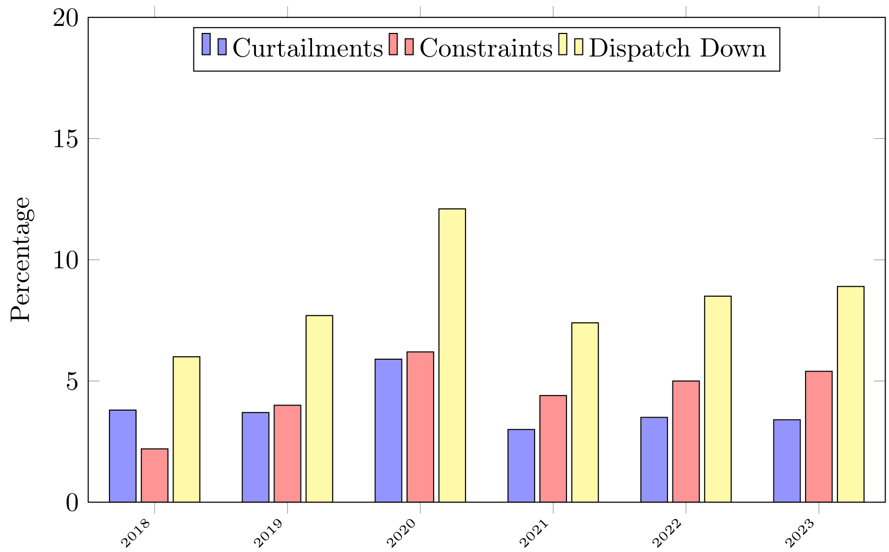


Fig. 1. Annual percentages of curtailments, constraints, and dispatch down incidents, illustrating the impact of renewable energy challenges on wind output [5].

- Our study evaluates the economic feasibility of four commercial BESS through a 15-year scenario analysis. This includes a detailed assessment of costs, returns, and evolving market conditions to guide decision-making.
- In brief, we explore the potential of quantile forecasts in energy markets, emphasising battery selection, trading strategies, and economic viability to empower market participants in dynamic electricity markets.

The rest of this paper is structured as follows: in Section 2, we refer to recent & salient DAM and BM PEPF publications. Section 3 gives a detailed breakdown of our DAM and BM dataset, including data relating to BESS. Section 4 provides an overview of our approach, models, specifics of the forecasting problem and of each trading strategy and their constraints. In the experimental results 5, we present trading strategy performance with a 10-year scenario analysis for four separate batteries. Finally, Section 6 concludes the paper with observations and suggested future work.

2. Literature review

This section surveys the relevant literature regarding electricity price forecasting and trading. In Section 2.1, we conduct an exploration of probabilistic forecasting, dissecting uncertainties prevalent in energy markets and providing a current overview of the field. Moving forward to Section 2.2, our focus shifts to the economic evaluation of energy storage systems within electricity markets. Finally, Section 2.3 scrutinises the intricate interplay of accurate forecasts and pragmatic constraints, shedding light on their pivotal role in the formulation of profitable trading strategies.

2.1. Probabilistic forecasting

PEPF is a critical component of energy markets, focusing primarily on price forecasting, which is informed by related forecasts such as load, wind, and solar generation. It aids in addressing uncertainties tied to various factors such as smart grids, renewable integration, and electric vehicle adoption [14,15]. In recent studies, best practices and evaluation metrics have been explored extensively [16]. Nowotarski and Weron [17] investigated various approaches, such as autoregressive models, neural networks, quantile regression averaging, and ensembles. They outline the use of metrics like pinball loss and interval score, emphasising the importance of reliability, sharpness, and rigorous out-of-sample testing. Marcjasz et al. [18] incorporated deep learning models into PEPF, highlighting the superiority of seasonal component models. Tzallas et al. [19] introduced a lightweight forecasting model for UK electricity prices. Marcjasz et al. [20] emphasised forecast averaging for enhanced accuracy, particularly with distributional deep neural networks. Monjazeb et al. [21] demonstrates QR's effectiveness in capturing price uncertainty in pay-as-bid markets under regional and climatic variations. Uniejewski and Weron [22] introduce of LASSO Quantile Regression Averaging (QRA), a method refining point forecasts using quantile regression with the LASSO model, and later smoothing QRA [23], with kernel estimation, outperforming benchmarks in reliability, precision, and economic value. Jiang et al. [24],Zakrzewski et al. [25] introduce a nonconvex regularised QRA and Factor QRA to improve EPF accuracy, particularly in PEPF. Janczura [26] present Expectile Regression Averaging as an alternative to traditional quantile-based approaches such as QR and QRA, demonstrating improved accuracy for EPF in the DAM.

The literature on probabilistic forecasting within the BM remains sparse, largely attributed to challenges in data acquisition. In a study by Klæ boe et al. [27], state-aware models such as SARMA and ARM were compared with purely time series-based models like ARMA and ARX. The results indicated that incorporating contextual information enhanced forecasting accuracy. However, these investigations often feature limited time horizons, typically extending only up to one hour ahead, leaving questions unanswered regarding longer-term forecasting in BMs. In the context of the Belgian electricity market, Dumas et al. [28] introduced a methodology for predicting imbalance prices, leveraging historical data, net regulation volume transition probabilities, and reserve activation information. Additionally, research such as [29] has delved into the predictability of BM prices using regime-switching models, revealing that BM prices display predictable behaviour, challenging the assumption of market efficiency. These insights suggest potential advantages for market participants in devising forecasting and trading strategies grounded in fundamental econometric relationships. Moreover, in a study conducted by Lucas et al. [30] focusing on BM price forecasting in Great Britain, machine learning techniques were employed, highlighting the efficacy of Gradient Boosting and Extreme Gradient Boosting algorithms. On the other hand, Narajewski [31] explored BM prediction in the German electricity market, uncovering that simplistic models often outperform sophisticated techniques.

2.2. Energy storage

Recent European electricity market reforms prioritise resilient mechanisms amid rising renewable energy integration [8]. The economic viability of energy storage systems in electricity markets has been examined in various contexts. Staffell and Rustomji [32] assessed the profitability of energy storage systems in the British electricity market, emphasising the role of reserve services. Tohidi and Gibescu [33] evaluated revenue from flow battery energy storage in photovoltaic (PV) solar plants, considering uncertainties in electricity prices and PV production. Abramova and Bunn [34] focused on battery storage trading and optimisation for enhanced profitability. Gräf et al. [35] investigated battery pack degradation, particularly the impact of temperature variations. On average, degradation occurred at 1.55% per year, with temperature-dependent rates ranging from 1.03% to 2.00% annually. Wankmüller et al. [36] incorporates degradation's arbitrage impact. More recently, Elalfy et al. [37] highlighted the potential of hybrid ESS to enhance energy storage performance, particularly for renewable energy integration and grid stabilisation, aligning with the dual-market strategies explored in this paper. Similarly, Amir et al. [38] propose optimal scheduling models and sustainable policies to address economic and environmental challenges, offering insights into the practical implementation of energy storage in volatile markets. Hu et al. [39] analyse the economic viability of BESS in European electricity markets, showing that while energy arbitrage remains constrained by current costs, BESS holds significant promise for frequency regulation services, especially in markets with less flexibility, such as Ireland.

2.3. Trading

In the domain of energy trading, crafting lucrative strategies for energy storage systems critically relies on precise probabilistic forecasts. Krishnamurthy et al. [40] performed a comprehensive analysis of trading models tailored for both DAM and BM arbitrage, emphasising the supremacy of stochastic models amid price uncertainty. Their models, including a Quantity-Only bid model and a Price–Quantity bid model, exhibited diverse levels of profitability and risk. In a parallel investigation, Narajewski and Ziel [41] delved into optimal bidding strategies within auction-based electricity markets, specifically for portfolios centred on renewable energy sources. Their research underscored the significance of market impact estimation and the consideration of transaction costs in shaping optimal strategies for risk-neutral traders. The analysis spanned various portfolios, encompassing wind and solar power producers, and showcased substantial revenue enhancements achievable with basic forecasting models. Recent advancements in electricity trading strategies have increasingly focused on integrating machine learning with traditional optimisation methods to improve scalability, adaptability, and decision-making under uncertainty. Multistage stochastic programming, as explored by Silva et al. [42], models future price curves and energy storage dynamics over multiple periods, allowing continuous strategy adjustments to account for market volatility and operational constraints. However, while effective, these approaches often face challenges with non-linearities and large datasets. To address this, machine learning models have been introduced to improve computational efficiency and scalability, although sensitivity to parameter tuning and lack of theoretical guarantees can limit applicability in regulated environments [43].

Mixed-Integer Linear Programming (MILP) has also emerged as a key tool for managing risk and optimising trading strategies across markets. It is widely applied to energy storage optimisation due to its ability to capture complementary constraints, such as the exclusivity of charging and discharging processes [44]. Recent work by Kraft et al. [45] demonstrates the versatility of MILP in balancing risk-neutral intraday market (IDM) strategies, which aim for profit maximisation, with risk-averse DAM strategies that mitigate exposure to volatility. Similarly, the inclusion of reinforcement learning with dynamic programming, as highlighted by Alghumayjan et al. [46], enhances real-time trading efficiency by enabling adaptive decision-making. These approaches contribute to aligning renewable energy storage systems with evolving market dynamics, improving grid stability and profitability [47].

While these approaches demonstrate significant strengths, our study prioritises computational efficiency and practical applicability by employing alternative probabilistic methods that better align with real-time forecasting challenges in dynamic markets. Notably, significant gaps remain in extending probabilistic forecasting techniques to the BM, where shorter forecasting horizons and heightened volatility pose practical challenges. By addressing these issues and aligning BM decisions with DAM strategies, our study provides a robust framework that enhances forecast reliability and improves dual-market trading performance.

3. Datasets

The dataset underpinning this study includes both market and battery data, enabling the comprehensive evaluation of trading strategies and economic viability. The input data was sourced from SEMO & SEMOpx, comprising historical and forward-looking data from 2019 to 2022. The dataset can be categorised into two main types of data: *Historic data* and *Forward/future-looking data*. Battery data incorporates technical specifications, costs, and degradation parameters, supporting scenario analyses over a 10–15 year horizon.

3.1. Day-ahead market

In our analysis, we focus on predicting DAM prices, with the forecast horizon starting at t and extending to the subsequent 24 settlement periods, denoted as:

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

Bids for the DAM are submitted at 11:00, and prices are announced at 13:00, with trading covering the 24-h period from 23:00 to 23:00 the following day.

Forward-looking data

Forward-looking data enables the model to anticipate price outcomes in the DAM based on projected supply and demand conditions. The dataset includes:

- *Demand Forecast (DF)* in MWh: TSO-provided 24-h demand forecasts capture daily and seasonal consumption trends, directly influencing market prices: $[DF_t, \dots, DF_{t+23}]$.
- *Wind Generation Forecast (WF)* in MWh: TSO-provided 24-h wind forecasts capture renewable variability, a key driver of price volatility in markets like the I-SEM: $[WF_t, \dots, WF_{t+23}]$.

Historical data

Historical data helps identify trends and behaviours critical to forecasting DAM prices. The dataset includes:

- *DAM Prices (DAMP)* in €/MWh: Prices from the previous 7 days (168 h) to capture short-term market trends: $[DAMP_{t-167}, \dots, DAMP_{t-1}]$.
- *Past Wind Forecasts (PWF)* in MWh: TSO wind forecasts from the previous 7 days to capture the impact of wind variability: $[PWF_{t-167}, \dots, PWF_{t-1}]$.
- *Past Demand Forecasts (PDF)* in MWh: TSO demand forecasts from the previous 7 days to account for consumption patterns influencing prices: $[PDF_{t-167}, \dots, PDF_{t-1}]$.

3.2. Balancing market

For the BM, we predict BM prices for the next 16 open settlement periods. The forecast horizon starts at $t+2$ as at time t, the market periods t and $t+1$ are already closed, and adjustments can only be made from $t+2$, denoted as:

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

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

Forward-looking data

Forward-looking data provides an anticipatory view of market conditions critical for predicting BM prices. The dataset includes:

- *Physical Notifications Volume (PHPN)* in MWh: Planned generation or consumption adjustments over the forecast horizon, influencing balancing actions: $[PHPN_{t+2}, \dots, PHPN_{t+17}]$.
- *Net Interconnector Schedule (PHI)* in MWh: Projected cross-border electricity flows, affecting supply–demand dynamics: $[PHI_{t+2}, \dots, PHI_{t+17}]$.
- *Renewable Forecast (PHFW)* in MWh: TSO forecasts of renewable output (e.g., wind and solar), critical due to variability: $[PHFW_{t+2}, \dots, PHFW_{t+17}]$.
- *Demand Forecast (PHFD)* in MWh: Expected electricity consumption, indicating periods of market tightness or surplus: $[PHFD_{t+2}, \dots, PHFD_{t+17}]$.
- *DAM Prices (DAM)* in €/MWh: Forward DAM prices for the next 8 h, signalling supply–demand expectations: $[DAM_{t+1}, \dots, DAM_{t+16}]$.

Historical data

Historical data captures past market behaviours to inform future price movements. The dataset includes:

- *Balancing Market Prices (BMP)* in €/MWh: Recent 24-h BM prices, reflecting market trends and price volatility: $[BMP_{t-51}, \dots, BMP_{t-3}]$.
- *Balancing Market Volume (BMV)* in MWh: Energy traded to balance the system over the past 48 periods: $[BMV_{t-51}, \dots, BMV_{t-3}]$.
- *Forecast Wind - Actual Wind (WDiff)* in MWh: Deviations between forecasted and actual wind generation over the last 48 periods, which drive price volatility: $[WDiff_{t-51}, \dots, WDiff_{t-3}]$.
- *Interconnector Flows (I)* in MW: Cross-border electricity movements over the past 48 periods, influencing price dynamics: $[I_{t-50}, \dots, I_{t-2}]$.
- *DAM Prices (DAM)* in €/MWh: Recent 24-h DAM prices adapted to half-hour settlement periods: $[DAM_{t-48}, \dots, DAM_{t}]$.

The variation in time intervals for historical data is due to availability, limited to the most recent and accessible 48 observations from the data source. For further details on our forecasting approach, market structure, datasets, and variables for both the DAM and BM, please refer to [48] and GitHub.[2]

3.3. Battery configurations

Battery data incorporates technical specifications, construction and operational costs, and maintenance expenses across four commercial configurations. This data supports scenario analyses of BESS over 10–15 years. Table 1 summarises the key specifications and costs of the batteries modelled: The CAPEX includes purchase, installation, commissioning, and ancillary costs, while O&M accounts for fixed and variable maintenance, assumed to grow at 2% annually. Degradation-related costs are modelled at 1.55% per year in line with lithium-ion battery data, with a maximum operational lifespan of 10–15 years. Market registration fees for ISEM participation are also included. This dataset supports the scenario analysis and profitability projections detailed in Section 5.2, offering insights into the economic viability of BESS across different configurations and trading strategies. For further details, see [49,50].

4. Methodology

In this section, we outline the methodology used in our study to investigate the development of BESS trading strategies. These strategies encompass the optimisation, and in some cases co-optimisation, of revenue streams derived from participation in ancillary service markets, energy-only markets, or both, while distinguishing these from the balancing prices charged by the TSO to balance responsible parties (BRPs). Just as ancillary service markets contribute to grid stability and reliability, BESS play an increasingly vital role in integrating renewable energy into the evolving energy landscape. To achieve this objective, our primary focus lies in the formulation of trading strategies aimed at maximising profits through energy arbitrage in the DAM and BM.

Methodology overview

In our analysis the forecasting & trading approach can be broadly viewed as comprising of 5 key steps for both the DAM and BM. That is:

1. *Data Collection and Preparation:* We gather historical and forward-looking data from the ISEM relating to the DAM and the BM.
2. *Data Pre-processing and Model Optimisation:* In preparation for analysis, we pre-process the data. Each predictive model undergoes hyperparameter tuning for each 3-month data subset to enhance its performance.
3. *Walk-Forward Model Validation:* For the reliability of our models, we employed a walk-forward validation process, iteratively updating the time horizon.
4. *Quantile Forecasting:* We generated quantile forecasts using our optimised models based on unseen test data. These forecasts were designed for a standard 24-h time horizon in the DAM. In contrast, the BM involved retraining models every 8 h to incorporate the most recent data while forecasting the next 16 settlement periods. This configuration reflects the unique requirements of the BM, where high volatility and shorter lead times demand frequent updates to maintain forecast accuracy. For further details on the differences between the DAM and BM forecasting approaches, see [48].
5. *Trading Strategy Execution:* With quantile predictions in hand, we implemented our chosen trading strategy. This strategy involved submitting quantity bids and offers for positions in both the DAM and BM, aligning with our 24 and 8-h forecasts.
6. *Economic Viability:* To assess the economic viability of the battery storage systems, we simulate and forecast trading profits over a two-year period and extrapolate these results to a 15-year battery lifespan.

[2] https://github.com/ciaranoc123/Balance-Market-Forecast

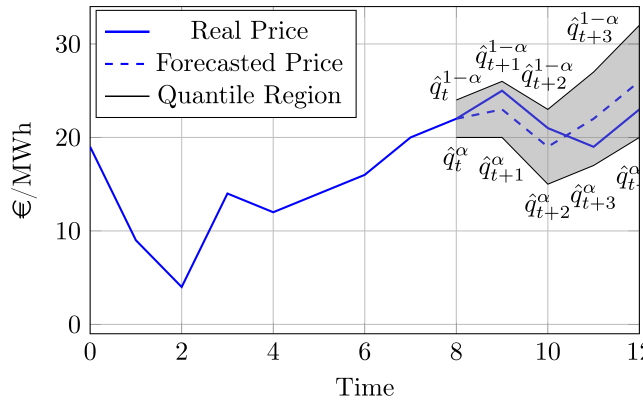


Fig. 2. Quantile forecast of electricity prices.

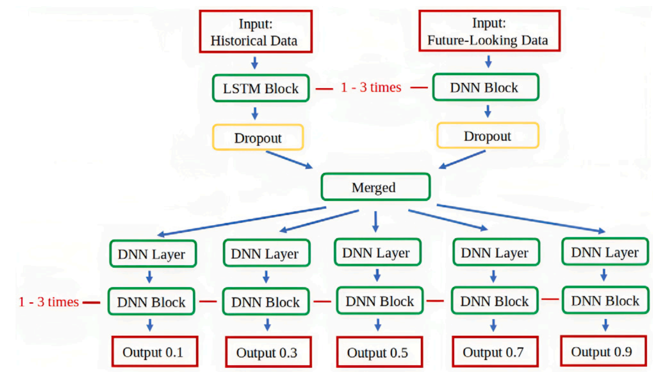


Fig. 3. MH RNN DNN Model.

To ensure empirical reliability, we utilised a back-testing framework that compares forecasted outcomes with actual market-clearing prices. This approach simulates real-world trading conditions, validating the alignment between forecast accuracy and trading performance. By strategically purchasing electricity during periods of low predicted prices, storing it, and reselling it during high-price periods, our methodology demonstrates the practical applicability and financial viability of the trading strategies in realistic market dynamics.

4.1. Quantile regression models

All models in our study employ quantile regression, a statistical technique for estimating conditional quantiles, allowing the estimation of target values at specific quantiles (e.g., 0.1, 0.3, 0.5, 0.7, 0.9). These quantiles are used to define a "quantile pair", $[\hat{q}_t^{\alpha}, \hat{q}_t^{1-\alpha}]$, which establishes a forecast range, encompassing lower and upper bounds, offering potential values within a specified confidence level. For instance, a quantile pair of 0.1 and 0.9, denoted by $q_t^{\alpha} = 0.1$ and its complementary quantile $q_t^{1-\alpha} = 0.9$, defines a forecast range that covers the central 80% of potential outcomes, providing a nuanced perspective on the distribution of forecast possibilities. See Fig. 2 for clarity.

A high-level categorisation of the models includes the following:

- *K-Nearest Neighbors* (KNN): A versatile non-parametric algorithm that predicts an instance's output by comparing it to the "K" nearest data points in the feature space, using distance metrics like Euclidean or Manhattan distance. The predicted value is the average of the K nearest data points in the feature space, making it suitable for capturing local patterns in time series data.
- *Random Forest* (RF): An ensemble learning method widely utilised in DAM and BM forecasting due to its ability to handle non-linearity and high-dimensional data. By aggregating the predictions of multiple decision trees, RF effectively captures complex temporal relationships and provides robust predictions for both short-term and long-term horizons.
- *Light Gradient Boosting Method* (LGBM): Like RF, Gradient Boosting methods have gained popularity in DAM and BM forecasting tasks for their efficiency and scalability. As a boosting algorithm, LGBM sequentially builds decision trees, iteratively improving model performance by focusing on data points with high residuals. This approach enables LGBM to capture intricate temporal patterns and make accurate predictions with minimal computational resources.
- *Deep Neural Network* (DNN): A versatile deep learning model equipped with customisable hyperparameters. It adeptly processes both historical data and future projections, facilitating accurate forecasting. Additionally, a hybrid variant merges LSTM and DNN architectures, enhancing predictive capabilities by capturing sequential patterns from historical data while effectively incorporating future trends [51]. The output layer predicts 8 h (or 16 timestamps). See Fig. 3 for visualisation.

We employed a consistent approach to hyperparameter optimisation, using grid search and cross-validation. We chose pinball loss as our loss function, as it directly aligns with the objectives of quantile-based forecasting. Hyperparameters were tuned across rolling 3-month data subsets, with model-specific configurations to ensure robustness. For KNN, we optimised the number of neighbours and distance metrics to balance adaptability and efficiency. For RF, the number of trees and maximum depth were adjusted to trade off overfitting and generalisation. LGBM parameters, such as learning rate and boosting iterations, were fine-tuned to capture intricate temporal patterns, while for DNN, the architecture was iteratively refined to balance complexity and performance with Talos. We employed a walk-forward validation framework, training models on past data and testing on unseen future data, reflecting real-world forecasting dynamics. For further details on the models' hyperparameter optimisation and forecasting approach, see [48].

4.2. Trading strategies

In this section, we present three trading strategies tailored to optimise profits in electricity markets while considering constraints and price dynamics, such as:

1. Trading Strategy 1 (TS1) follows a rule-based heuristic approach, utilising a straightforward single trade strategy. This strategy ensures that the buy timestamp precedes the sell timestamp.
2. Trading Strategy 2 (TS2) maintains TS1's constraints whilst increasing intraday trading frequency with an iterative multi-trade approach.
3. Trading strategy 3 (TS3) is an optimisation-based high-frequency approach that enables flexible buy/sell timestamps while maintaining bottleneck-constrained purchase and sell volumes.

Our trading strategies are separately applied to both the DAM and the BM. In Section 4.6, we present an adapted approach for holding DAM and BM positions concurrently.

4.3. TS1: Single trade quantile strategy

TS1 is a rule-based heuristic trading strategy adopted from [22, 23], incorporating the same BESS constraints. This strategy employs quantile-based forecasts to optimise trading decisions involving a hypothetical battery with capacity B_c, no discharge limit, discharge efficiency $\mathcal{E}_d$, and charge efficiency $\mathcal{E}_c$. Over the time horizon of interest (i.e. 1 day for the DAM or 8 h for the BM), a single buy–sell pair trade

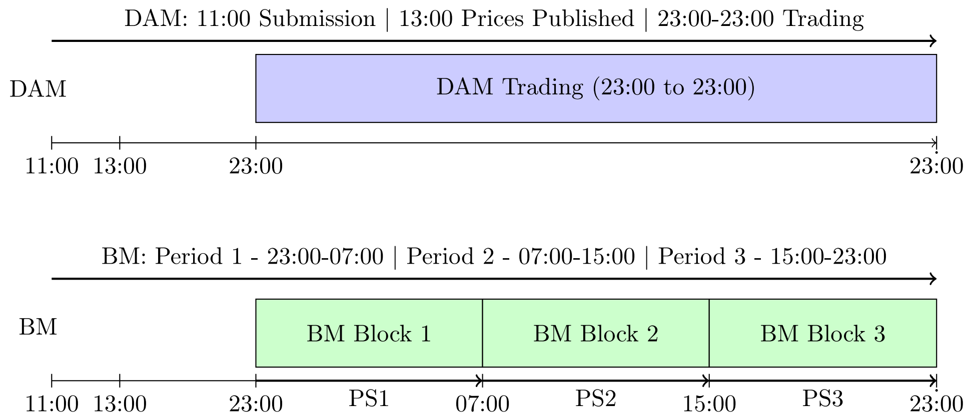


Fig. 4. Aligned DAM and BM trading timelines with submission and trading details.

is permitted with the requirement that the buy trade occurs before the sell trade. The buy/sell order constraint ensures that all trades maintain logical consistency, reflecting the requirement that batteries must purchase energy before selling. This constraint is particularly important for scenarios where batteries begin with a zero state of charge, necessitating sequential charging and discharging operations. The key steps for TS1 are as follows:

1. *Identify Optimal Timestamps:* Determine timestamps for the minimum and maximum predicted prices for the specified quantile, q_t^{α}, and the complementary quantile, $q_t^{1-\alpha}$. Choose the pair with the greater difference.
2. *Execute Trades:* Submit buy and sell orders at identified timestamps.
3. *Calculate Profit:* Calculate profit as the difference between the sell and buy prices, adjusted for charge $\mathcal{E}_c$ and discharge $\mathcal{E}_d$ efficiencies.

The objective of the trading strategy is to maximise the expected profit by leveraging the quantile pair, $[\hat{q}_t^{\alpha}, \hat{q}_t^{1-\alpha}]$, forecasted prices, which are chosen to capture profitable trading opportunities based on predicted price levels. The objective function for this trading strategy is defined as:

$$\max \sum_{t=1}^{T} \left(\mathcal{E}_d \cdot \hat{q}_{t_2}^{\alpha} \cdot - \frac{\hat{q}_{t_1}^{1-\alpha} \cdot}{\mathcal{E}_c} \right) \tag{3}$$

where $\hat{q}_t^{\alpha}$ represents the model-predicted α-quantile price at time t, and $\hat{q}_t^{1-\alpha}$ denotes the complementary $(1-\alpha)$-quantile, which corresponds to the higher quantile price prediction, used here for comparison in deciding profitable trades. DAM trading involves a 24-h forecast horizon with hourly granularity, while BM trading operates on an 8-h forecast horizon with half-hourly granularity, starting two intervals after the initial timestamp. This corresponds to 24 time periods for the DAM and 16 for the BM. See Fig. 4 for clarity.

4.4. TS2: Multi-trade strategy

TS2 extends TS1 by iteratively identifying multiple buy–sell pairs for the 24-h period in DAM or 8-h period in BM, maintaining the rule that buy timestamps precede sell timestamps while increasing intraday trading frequency. The first three steps of TS2 are consistent with TS1. The subsequent three steps are specific to TS2 and outlined below:

4. *Create Additional Price Subsets:* To adhere to the buy/sell constraints, the price data is divided into subsets. Subset division is based on temporal segmentation, separating data before and after the first trade identified in TS1. This ensures new buy–sell pairs are found within defined intervals, minimising overlap and enabling better utilisation of the trading horizon.
5. *Identify Buy–Sell Pairs:* Within each subset, as in TS1, identify the timestamps for the minimum and maximum predicted prices corresponding to $\hat{q}_t^{\alpha}$ and $\hat{q}_t^{1-\alpha}$. Quantile pairs are used to balance risk and reward, identifying trades where the price difference is most significant within the subset. For each pair, submit buy and sell orders for the trade with the greatest price difference, ensuring adherence to the buy/sell order constraint.
6. *Calculate Profit:* Calculate profit for each trade pair as the difference between the sell and buy prices, adjusted for battery charge/discharge efficiency, as in TS1. This calculation incorporates all valid trade pairs identified across subsets, summing the profits for the overall strategy.

While TS2 offers more trading opportunities than TS1, it is limited by the buy/sell order constraint.

4.5. TS3: High-frequency strategy

TS3, inspired by Staffell and Rustomji [32], introduces an optimisation-based approach designed to tackle the inherent limitations of battery ramp rates. This challenge is particularly pronounced in larger batteries, where a full charge or discharge within a single trading cycle is typically unfeasible. By incorporating a bottleneck mechanism, TS3 enables greater flexibility in determining buy and sell timestamps, thereby removing the constraint requiring buy timestamps to precede sell timestamps. The bottleneck within our research encompasses several realistic limitations. The ramp rate R is restricted by factors including the battery's capacity and maximum allowable charging speed, limiting energy acquisition during specific intervals. Similarly, the discharging rate faces constraints linked to the battery's state of charge and the maximum discharging rate, affecting energy release. Battery capacity dictates the volume of energy available for trading. To ensure battery health and reliability, a minimum charge level constraint is in place. Additionally, energy efficiency (denoted as $\mathcal{E}d$ and $\mathcal{E}c$) causes energy losses during charging and discharging. These limitations define the operational boundaries of our trading strategy and are vital for its performance. The key steps of TS3 can be summarised as follows:

1. *Find Min and Max Price Periods:* As in TS1 & TS2, this step involves identifying timestamps for the minimum predicted price associated with a specified quantile ($\hat{q}_t^{\alpha}$) and the maximum predicted price for the complementary quantile ($\hat{q}_t^{1-\alpha}$). However, the order of timestamps is now flexible.
2. *Charging/Discharging Bottleneck:* This step focuses on the charging and discharging bottleneck. When the minimum price period precedes the maximum price period or vice versa, the algorithm dynamically adjusts the charging and discharging operations accordingly to maximise profitability. Further details on this bottleneck and the associated profit calculations are available in Algorithm 1.

3. *Iterate for Additional Trade Pairs:* The algorithm applies the same process to subsets of price data before, after, and in between each trade pair. This iterative approach allows for the exploration of additional trading opportunities and price subsets.
4. *Repeat for All Trade Pairs:* Continue iterating through all subsets until no more purchase and sell pairs are available.

Algorithm 1 Algorithm 1: TS3 Bottleneck

Initialize variables: c *(charge level)*, x_{buy} *(charging quantity)*, x_{sell} *(discharging quantity)*, p_{min} *(min price)*, p_{max} *(max price)*, *Profit*
Initialise constants: R *(ramp rate)*, B_c *(battery capacity)*, C_{min} *(min charge level)*
Charging/Discharging Bottlenecks
if Period of p_{min} < Period of p_{max} **then**
  Charging Strategy:
  $x_{buy} \leftarrow \min(B_c - c,\ R)$ ▷ Charging Bottleneck
  $c \leftarrow c + x_{buy}$
  $x_{sell} \leftarrow \min(c - C_{min},\ R)$ ▷ Discharging Bottleneck
  $c \leftarrow c - x_{sell}$
  Profit $\leftarrow (p_{max} \times x_{sell} \times \mathcal{E}_d) - (\frac{p_{min} \times x_{buy}}{\mathcal{E}_c})$
else
  Discharging Strategy:
  $x_{sell} \leftarrow \min(c - C_{min},\ R)$ ▷ Discharging Bottleneck
  $c \leftarrow c - x_{sell}$
  $x_{buy} \leftarrow \min(B_c - c,\ R)$ ▷ Charging Bottleneck
  $c \leftarrow c + x_{buy}$
  Profit $\leftarrow (p_{max} \times x_{sell} \times \mathcal{E}_d) - (\frac{p_{min} \times x_{buy}}{\mathcal{E}_c})$

The trading strategy outlined addresses these limitations by dynamically adjusting charging and discharging operations based on the order of minimum and maximum price periods, aiming to maximise profits under the constraints imposed by the bottleneck, thus significantly boosts trading frequency.

4.6. TS3-Dual: Dual markets

Our dual markets approach, *TS3-Dual*, optimises trading decisions in both the DAM and BM concurrently, ensuring synchronisation between them. This strategy capitalises on the differences in granularity and lead times, such as:

- DAM positions are determined at time t for the time range of $t+12$ to $t+36$, with hourly granularity, covering a 24-h period.
- BM positions, in contrast, are generated at time $t+12$, 12 h after DAM positions have been established. These BM positions are based on an 8-h ahead forecast extending to $t+20$, with half-hly granularity.

The emphasis in TS3-Dual is on midday trading opportunities in the DAM, while the remaining time before and after DAM trades is allocated to the BM, capitalising on BM's consistent volatility. To achieve this, we create subsets of price data to optimise trades in both the DAM and BM, divided as follows:

- Early-Bidding in the BM (PS1): Tailored for BM trades, PS1 focuses on time periods occurring before any DAM trades. It provides an opportunity for strategic planning and early bidding to optimise trading decisions in the BM market.
- DAM Trades - PS2: Dedicated to the DAM, this subset covers the time range starting from the initial DAM trade pair's minimum period to the maximum period.
- Late-Bidding in the BM - PS3: Similar to PS1, PS3 serves BM trades but encompasses periods after DAM trades. It is strategically positioned to accommodate late bidding activities in the BM.

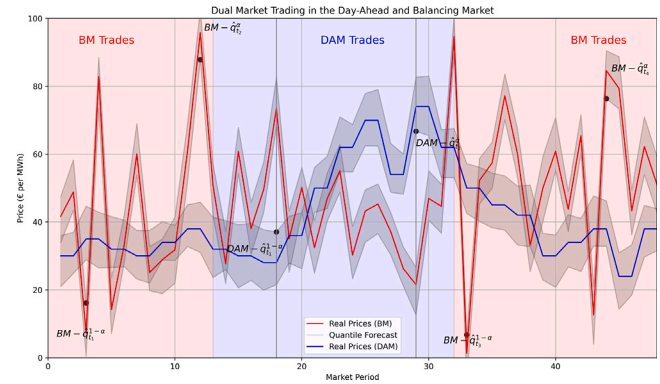


Fig. 5. TS3-Dual Strategy.

We follow the outline for TS3 in each subset, iterating through all subsets until no more purchase and sell pairs are available. Organising price data into these subsets enables TS3-Dual to efficiently manage trading opportunities in both the DAM and BM while ensuring synchronisation between them, as can be seen in Fig. 5. We also implemented the same three strategies using a more complex MILP trading approach [47] instead of the heuristic presented above. The focus of the paper is to compare the trading strategies using the same algorithm, and the MILP approach provides findings that are in line with those of the heuristic, so for the sake of brevity, we included them in Appendix. Code for all trading strategies and algorithms can be found at GitHub.[3]

5. Experimental results

In this section, we present the results of our study, focusing on the practical applications of quantile forecasts in BESS trading within the DAM and BM. Our analysis evaluates three distinct trading strategies: TS1, TS2, and TS3, each incorporating quantile forecasts alongside trading constraints to optimise efficiency. Subsequent sections offer a detailed exploration of these strategies, exploring quantile pair selection, model choice, forecast accuracy, and highlighting key distinctions between the DAM and BM that influence trading outcomes. Furthermore, we conduct a thorough BESS economic analysis, highlighting the economic implications of these strategies within the DAM and BM.

5.1. Trading strategies

Our evaluation of TS1, TS2, and TS3 incorporates a hypothetical battery with a capacity B_c of 1 MWh, an 80% discharge efficiency ($\mathcal{E}_d$), and a 98% charge efficiency ($\mathcal{E}_c$). Each strategy is tested over a period spanning mid-2019 to mid-2022, covering both the Irish DAM and BM. To ensure only profitable trades are executed, each strategy includes a minimum expected profit threshold. Specifically, a trade is executed only if the expected profit, calculated as $\mathcal{E}_d \cdot \hat{q}^{\alpha}_{t_2} - \frac{\hat{q}^{1-\alpha}_{t_1}}{\mathcal{E}_c}$, is non-negative. This threshold is particularly crucial in the BM, where increased volatility and unpredictable price dynamics amplify the risk of unprofitable trades. Furthermore, TS2, TS3, and TS3-Dual limit trading activity to a maximum of three trades per day, provided each trade meets the expected profit threshold. This limit is designed to prevent over-trading in low-margin conditions, enhancing trade quality and supporting more consistent profitability across both markets.

TS3 emerges as the top-performing strategy in both the DAM and BM, as illustrated in Fig. 6, surpassing TS1 and TS2 in profitability. This

[3] https://github.com/ciaranoc123/DAM-BM_Trading

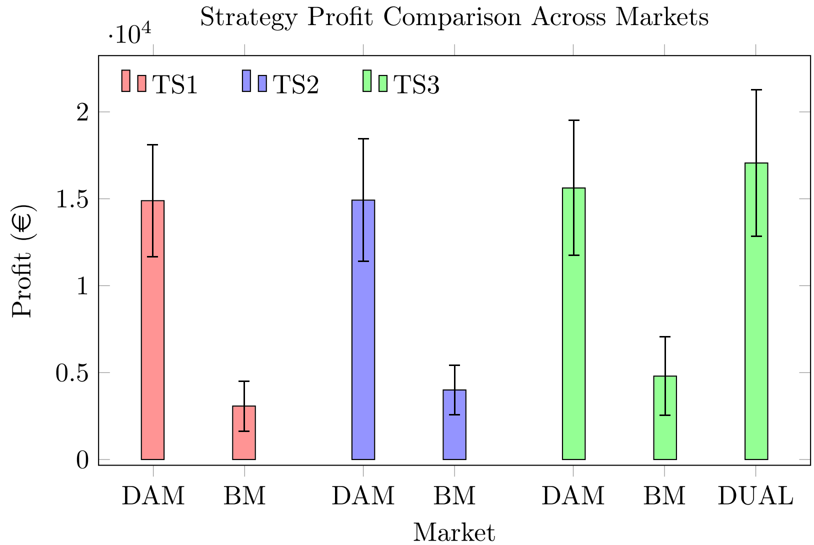


Fig. 6. Average profit for TS1, TS2, & TS3 in each market. Error bars highlight the range for each quantile pair.

improvement is due to TS3's flexible timestamp order, which enables increased trading frequency compared to TS2, proving fundamental to maximising profits in a quantile-based context. By enabling non-sequential timestamp orders, TS3 capitalises on price fluctuations and manages battery state constraints more effectively than TS1 and TS2. Despite the heightened risk in the BM of trades falling short of the expected profit threshold, TS3 demonstrates a more aggressive profit increase than TS1 and TS2 due to the BM's half-hourly market structure, offering more trading opportunities compared to the DAM. TS3's ability to adjust buy/sell pairs based on quantile forecasts while managing battery constraints allows it to navigate BM's fluctuating conditions more effectively.

The inclusion of TS3-Dual, which synchronises trading between the DAM and BM, underscores the advantages of market diversification in energy trading by splitting trading windows across both markets to mitigate market-specific risks. This dual-market strategy leverages BM's intraday price fluctuations to identify profitable trades beyond the DAM alone. Table 2 provides a breakdown of financial outcomes achieved by TS3, evaluated across various quantile pairs and markets over the year. These results demonstrate each strategy's performance relative to benchmarks, including perfect foresight (PF) as the theoretical maximum profit achievable and the baseline quantile pair (0.5–0.5).

Trading in the day-ahead market

Across the selected trading strategies, all yield greater profits in the DAM than in the BM, with TS3 consistently outperforming TS1 and TS2, as shown in Fig. 6. Our analysis of TS3 in the DAM (Table 2) reveals that the baseline 0.5–0.5 quantile pair achieves the highest or near-highest profitability across all models. For KNN and LGBM, the 0.5–0.5 pair outperforms other quantile combinations, while for RF and DNN, it falls only slightly short of optimal pairs. This configuration produces the highest average profit of €17,011 across all models, capturing roughly 60% of the maximum potential profit (€28,212).

The relatively low error rates in the DAM limit the impact of quantile selection on profitability, suggesting that accounting for volatility is less critical than in the BM, where quantile selection has a more pronounced effect. In practical terms, this suggests that traders in the DAM could benefit more from focusing on efficiency-based strategies rather than complex quantile optimisations, as returns on such adjustments are modest in a more stable market environment.

Trading in the balancing market

In contrast to the DAM, the BM benefits more from quantile-based strategies due to its inherent volatility and forecasting challenges. Within TS3, as shown in Table 2, the 0.5–0.5 quantile averages €6003, approximately 8% of the benchmark €71,669 achieved with PF. Higher quantile pairs such as 0.7–0.9 and 0.5–0.7, however, outperform this baseline 0.5–0.5 quantile pair. Specifically, the 0.7–0.9 quantile pair achieves the highest average profit of €7052, approximately 9.8%, while the 0.5–0.7 pair follows closely with €6966, representing 9.7%. The 0.7–0.9 quantile pair is the top-performing choice for RF and LGBM, while KNN shows its best results with the 0.5–0.5 quantile, and DNN performs best with the 0.5–0.7 pair. This pattern suggests that higher quantile pairs may better capture extreme price values aligned with the BM's volatile nature, though results vary significantly among quantile pairs for TS3 and are highly model-dependent, as illustrated in Fig. 7.

While BM's profitability consistently lags behind the DAM and PF benchmarks, with the best result achieving approximately 9.8% of the potential €71,669 from PF, this discrepancy highlights the forecasting difficulty and unpredictable nature of the BM. Nevertheless, it underscores the substantial, though challenging, profit potential for market participants who can accurately forecast in this volatile environment. The BM's frequent price spikes and dips present unique opportunities; with advanced models and strategic quantile choices, traders can capitalise on these fluctuations. However, success demands precision and adaptability, as even small forecasting errors can impact profits.

Trading dual market positions

In the dual market approach, TS3-Dual capitalises on both the stability of the DAM and the volatility of the BM, aligning positions across both markets to maximise returns. As detailed in Table 2, the baseline 0.5–0.5 quantile pair consistently produces high profitability, achieving €18,810 and capturing 22.7% of the potential profit of €82,683. The 0.3–0.5 quantile pair follows closely, averaging €18,648, or 22.5% of the profit potential. This result highlights the adaptability of TS3-Dual in leveraging straightforward quantile pairs effectively, even as market conditions vary between the DAM and BM.

The LGBM model emerges as the top performer in TS3-Dual, attaining a profit of €21,250 with the 0.5–0.5 quantile pair, equivalent to 25.7% of the profit potential with PF. While the DAM achieves a higher percentage of profit potential alone (60%), its total profit remains lower compared to the dual market approach, highlighting the benefits of combining the DAM's stability with the BM's higher-reward

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

	Financial profits from TS3: bottleneck-controlled strategy									
	Quantiles $[\hat{q}_t^{\alpha}, \hat{q}_t^{1-\alpha}]$	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
Market	**Model**									
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 α	**€17,011**	€15,528	€16,996	€15,984	€15,734	€15,983	€12,120	€28,212	€15,622
BM	Average α	€6,003	€3,913	€5,511	€6,966	**€7,052**	€4,107	€23	€71,669	€4,797
DUAL	Average α	**€18,810**	€16,700	€18,648	€18,073	€17,848	€17,213	€12,126	€82,683	**€17,060**

potential, resulting in a more profitable outcome. Although the BM alone generates the lowest returns and percentage of the profit potential (9.8%), its inclusion in the dual market strategy raises total profits beyond what is achievable in either market individually. This outcome confirms the economic value of dual-market trading, with TS3-Dual consistently outperforming single-market strategies across all quantile pairs, as illustrated in Fig. 6.

Performance of non-conventional quantile pairs

In analysing the performance of non-conventional quantile pairs for the DAM, BM, and Dual market strategies, it becomes apparent that the non-conventional pairs (e.g., 0.3–0.5, 0.5–0.7, 0.7–0.9) provide more varied profit outcomes compared to conventional pairs (e.g., 0.5–0.5, 0.3–0.7, 0.1–0.9), see Fig. 7. For DAM, non-conventional pairs show a relatively stable profit profile, with quantile pairs like 0.3–0.5 and 0.5–0.7 performing comparably to conventional pairs in terms of overall profitability and consistency. However, as seen from the narrower error bars in the DAM profits, these non-conventional pairs offer greater stability and less variability across different forecasting models, making them less sensitive to model-specific biases or fluctuations in predictions.

In contrast, the BM shows lower profits and higher variability across both conventional and non-conventional pairs. Non-conventional pairs like 0.5–0.7 and 0.7–0.9 yield slightly higher profits than conventional pairs, though large error bars indicate model-dependent uncertainty. While the Dual strategy yields the highest profits for the baseline 0.5–0.5 quantile pair, non-conventional quantile pairs, particularly 0.3–0.5 and 0.5–0.7, also achieve consistent profits with moderate variability. Despite a general association between higher profits and increased variance in some pairs, these unconventional pairs effectively capture price fluctuations and manage risk, proving ideal for Dual market strategies.

Model selection and forecast accuracy

This section highlights the importance of analysing model performance, forecast accuracy, and model selection to maximise profitability across different energy markets. Plot 8 illustrates the profit performance for different models (KNN, DNN, LGBM, and RF) for TS3 in the DAM, BM, and DUAL markets approach. In the DAM, the RF and LGBM models yield the highest profits with moderate variation, indicating stable performance across quantile pairs. The BM shows significantly lower profits for all models, with substantial variability, suggesting a high sensitivity to quantile pair selection and a less predictable environment. In the DUAL approach, RF and LGBM also perform well, with narrower error bars than BM but wider than DAM, showing a balance between profitability and sensitivity to quantile pairs. These

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

results suggest that the RF and LGBM models are preferable for achieving stable outcomes in the DAM and BM markets, as well as in the combined DUAL approach.

The plot 9 highlights a trend between model accuracy (measured by pinball score) and profit across TS3 for the DAM, BM, and DUAL market approach. For TS3 in the DAM and TS3-DUAL, lower errors correlate strongly with higher profits, emphasising the impact of precise forecasting. However, the BM shows a weaker relationship between accuracy and profit among the top three models; lower accuracy does not correspond as strongly with increased profits, suggesting that factors beyond forecast accuracy may play a significant role in profitability here. These findings underscore the fundamental role of forecast accuracy in driving profitability across the DAM, BM, and DUAL market approach, emphasising the need to prioritise high-accuracy models.

Table 3 highlights the performance of QR models in the DAM and BM markets using the Aggregate Pinball Score (APS). LGBM consistently achieved the lowest APS in both markets (3.62 for DAM, 12.48 for BM), demonstrating its capability to capturing price uncertainty across varying market conditions. RF also performed well, closely trailing LGBM, while KNN exhibited the highest APS in both markets, indicating its limitations in handling the complexity and volatility of electricity prices, particularly in the BM. The higher average APS in the BM (13.10) compared to the DAM (4.66) underscores the greater forecasting challenges in the BM.

Improved dual-market strategies

This study addresses key limitations in existing dual-market trading strategies by integrating realistic forecasting horizons and practical constraints, bridging gaps often overlooked in prior research. Traditional approaches, such as [40,52,53], frequently assume unrealistically long BM forecasting horizons, which are impractical in real-world, highly volatile market conditions [30,31,48]. In contrast, our methodology aligns BM trading decisions with DAM strategies by incorporating real-time forecasting and constraints that reflect actual market dynamics. This approach not only enhances forecast accuracy and trading

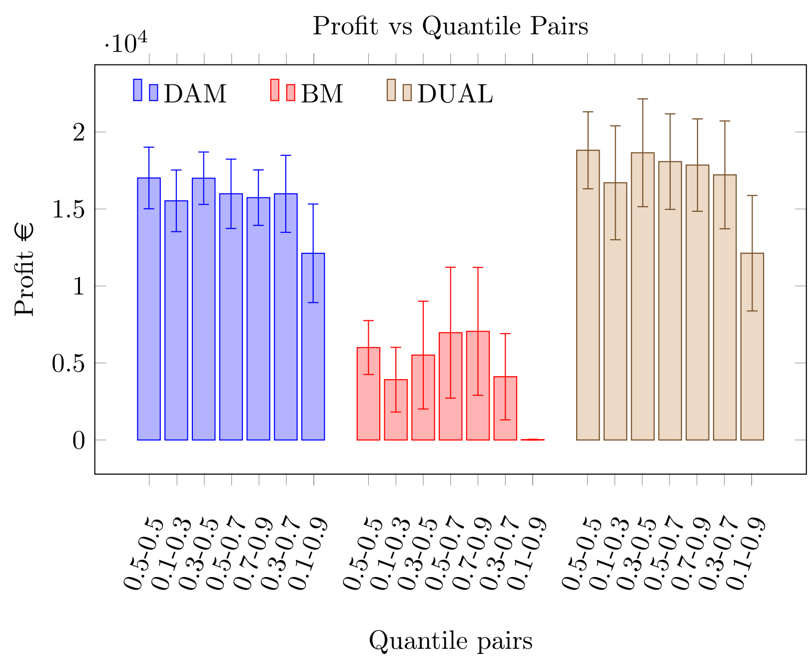


Fig. 7. TS3 Profit for DAM, BM & DUAL quantile pairs. The error bars are relative to the different forecasting models.

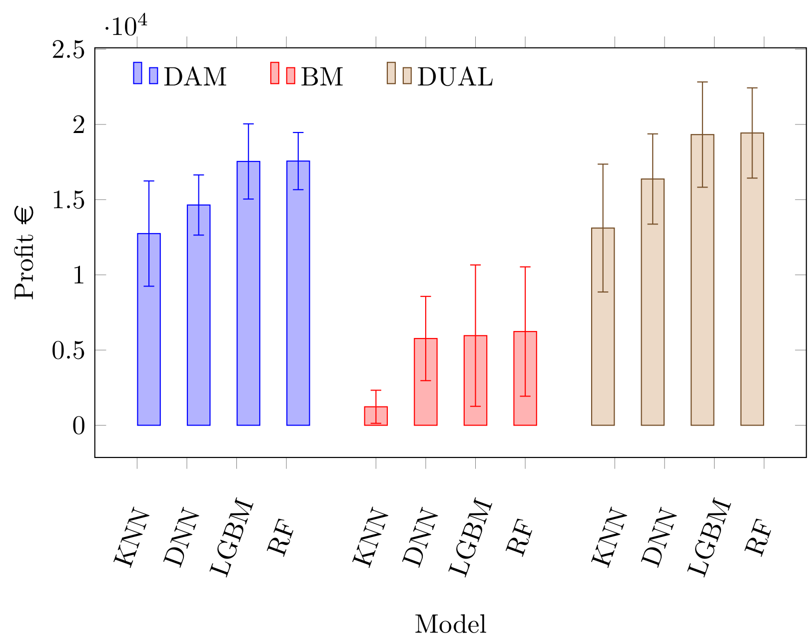


Fig. 8. TS3 profit for models in the DAM, BM & Dual with range in quantile pair.

outcomes but also demonstrates the practicality of dual-market integration using real datasets. Furthermore, while heuristic methods combined with machine learning models improve adaptability in dynamic markets [34], they lack the theoretical guarantees of exact methods and may underperform in highly regulated environments [43]. By leveraging QR and hybrid optimisation, our study achieves a robust balance between adaptability and reliability, producing both effective and practical trading strategies for the DAM and BM.

5.2. Economic viability - scenario analysis

In this section, we present a comprehensive analysis of the economic viability of BESS configurations, exploring various factors that influence their returns and performance. Our study encompasses a scenario analysis focusing on key elements such as construction costs, maintenance expenses, degradation-related costs, efficiency losses, and market dynamics. The goal is to evaluate the profitability and economic outlook of different BESS units over a potential lifespan of 10–15 years. In the following discussion, as detailed in [49,50], we explore key factors influencing the returns derived from operating a BESS. These include:

- CAPEX: Battery purchase, including ancillary systems, installation, commissioning, permits, and civil works.
- Fixed O&M (€kW-year): Fixed maintenance costs and variable costs throughout the system's lifespan, based on operation hours or cycles. All batteries are modelled to have maintenance costs increasing at a rate of 2% per year, as per the Sandia report [54].

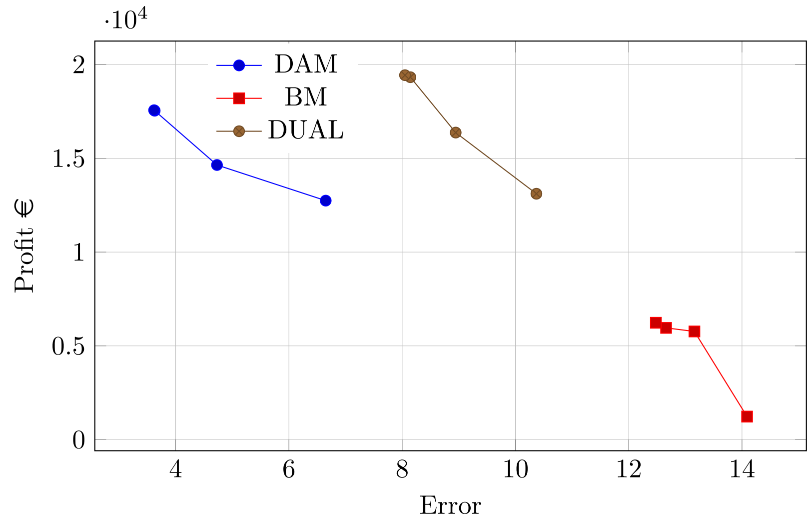


Fig. 9. TS3 Aggregate Pinball Score of Model vs Profit.

- Degradation-related costs: Expenses due to cycle-induced degradation, potentially requiring cell addition or replacement, leading to reduced battery capacity and efficiency over time. Battery degradation is estimated at 1.55% in line with lithium-ion battery data from [35].
- Efficiency costs: Costs related to round-trip efficiency losses (€/kWh). All battery options are modelled with a 95% charge & discharge efficiency.
- Depth of Discharge: Energy discharged as a percentage of rated capacity.
- Ramp Rate: Ratios of rated energy to rated power, e.g. 2-h Tesla megapack, 1-h lithium-ion battery in [54].
- Calendar Life (years): Maximum lifespan from factors such as state of charge, e.g., Li-ion batteries end life below 60% rated energy. All batteries have an assumed lifespan of ~10-15 years.
- Market registration costs for trading in ISEM DAM and BM include an annual total of €18,294. These costs consist of a once-off entry fee, annual subscription fees, BM accession fee, BM participation fee, and variable trading fees, which apply per MWh traded. For a detailed fee breakdown, see [55] for ISEM DAM & IDM and [56] for BM.

Items we will not factor in for issues on acquiring accurate data include:

- Warranty: (€/kWh-year): Annual fees for quality assurance.
- Insurance (€/kWh): Premiums against unforeseen risks.
- End-of-life costs: Expenses for disassembly, transportation to recycling facilities, and safe disposal of lithium-ion cells.
- Subsidies and government incentives: Potential financial support mechanisms to offset initial investment costs vary in availability and impact.

Battery options

We analyse various battery options, utilising configurations provided in [57], including smaller batteries with capacities of 3MWh (Scottish Power, Battery A) and 3.9 MWh (Tesla Megapack, Battery B) and larger batteries with capacities of 10MWh (Avolta storage, Battery C) and 39 MWh (10 T Megapacks, Battery D). Revenue data for all batteries is derived from the leading dual-market model in TS3-Dual, utilising configurations specific to the selected battery setup.

Smaller batteries: A & B

- Battery A, Scottish Power (3 MWh) - This battery features a 1-h cycle, a maximum discharge capacity of 3 MWh, and operates with a charge/discharge efficiency of 95%. With a construction cost of €1,671,000.00 (€557 per kWh) and annual maintenance expenses of €11,000 (€4 per kWh), it represents a compact and efficient option suitable for applications with shorter duration requirements.
- Battery B, Tesla Megapack (3.9 MWh) - Designed for a 2-h cycle, Battery B shares similar charge/discharge efficiencies and ramp rates with Battery A. Its purchase costs amount to €1,722,628.98 (€447 per kWh), and annual maintenance costs are €7730.96 (€2 per kWh). The extended capacity makes it well-suited for applications demanding longer discharge periods.
- Battery C, Avolta Storage (10 MWh) - This battery is configured with a 1-h cycle, a maximum discharge capacity of 9 MWh, and a charge/discharge efficiency of 95%. With a construction cost of €4,850,000 (€485 per kWh) and annual maintenance costs of €100,000 (€10 per kWh), designed to balance capacity and efficiency, catering to applications with larger scale and short duration requirements.
- Battery D, Tesla Megapack*10 (38.5 MWh) - A larger-scale option, features a 2-h cycle and shares similar charge/discharge efficiencies and ramp rates with Battery B. The purchase cost, accounting for a bulk discount for ordering 10 units, is €13,726,186.17 (€356 per kWh), with annual maintenance costs of €61,593.89 (approximately €2 per kWh). This configuration, suitable for substantial energy storage needs, highlights the potential economic benefits of scaling up BESS installations.

Economic viability of BESS units

This section assesses the economic viability of various BESS configurations, focusing on profitability timelines and performance over a 10–15 year lifespan. Fig. 10 illustrates the 15-year return on investment for batteries A and B. Fig. 11 compares the 15-year returns for batteries C and D.

1. A 3 MW Scottish Power unit with construction costs of €557/kW and maintenance costs of €11/kW, does not achieve profitability until year 12, with a 16% return by year 15.
2. A 3.9 MW Tesla Megapack with construction costs of €447/kW and maintenance costs of €2/kW, does not achieve profitability until year 11, with a 34% return by year 15.
3. A 10 MW Avolta Storage unit with construction costs of €485/kW and maintenance costs of €10/kW, achieves profitability by year 11, with a 38% return by year 15.

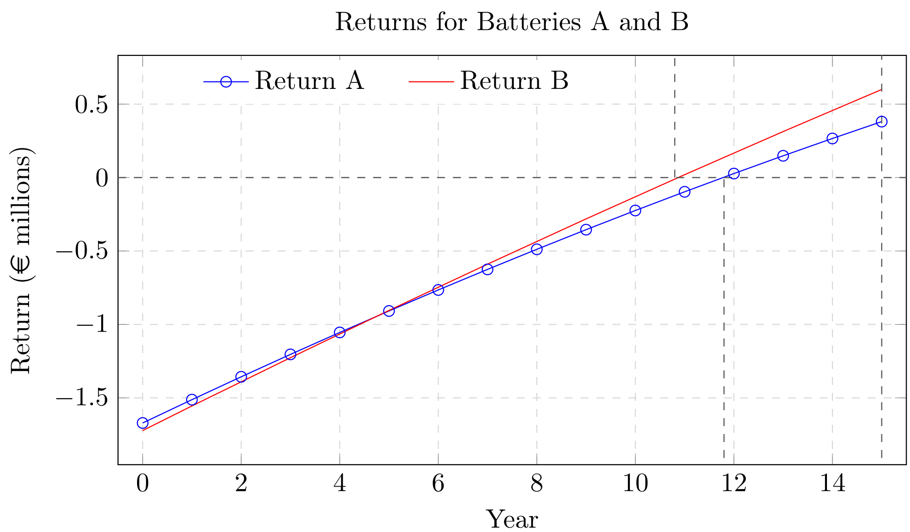


Fig. 10. 15-year cost breakdown for the 3 MW Scottish Power and 3.9 MW Tesla capacity.

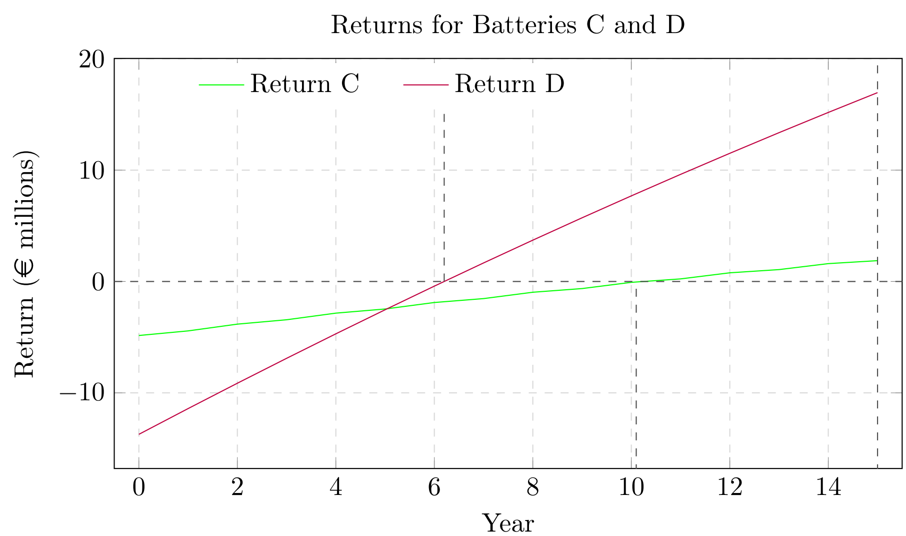


Fig. 11. 15-year cost breakdown for Avolta Storage (C) and Tesla MegaPacks (D) totalling 38.5 MWh.

4. A 38.5 MW Tesla Megapacks unit with construction costs of €356/kW and maintenance costs of €2/kW, achieves profitability by year 7, a return of 56% by year 10 and 123% by year 15. The results emphasise the impact of size and cost dynamics on BESS economic outlook.

The findings highlight the evolving landscape of BESS and the crucial role of cost reduction. When considering potential interest in construction and maintenance costs, Batteries A and C point towards alternative investment opportunities. In contrast, Batteries B and, notably, Battery D exemplify economic viability. These results underscore the recent advancements in BESS cost-effectiveness and emphasise the significance of appropriate battery sizing. They reveal the intricate link between construction and maintenance expenses, battery size, and long-term profitability, shaping the future of energy storage technologies and their grid integration.

Limitations

Key assumptions in this study include consistent annual profit levels derived from trading outcomes, despite inherent market variability and potential changes in market dynamics over time. Battery degradation is modelled at an annual rate of 1.55% [35], without considering accelerated degradation due to high cycling frequencies or extreme operating conditions. While CAPEX, operation and maintenance costs, and round-trip efficiency losses are factored in, the analysis does not account for potential cost reductions in battery technology or improvements in storage efficiency. Similarly, market assumptions include stable energy price structures and regulatory conditions over the 15-year period, excluding the potential impacts of increasing renewable penetration, regulatory changes, or evolving grid demands. Additionally, trading strategies rely on historical data, which may not fully capture future market conditions, such as increased competition in balancing markets or shifts in market liquidity.

Furthermore, the analysis excludes co-optimisation of ancillary services or emerging revenue streams that could complement arbitrage strategies. External economic factors, such as inflation, currency fluctuations, and geopolitical risks, are also not addressed. Finally, the study does not incorporate the role of subsidies or policy incentives, which are often essential for addressing the high CAPEX of battery systems and ensuring economic viability. As highlighted by [58], financial mechanisms such as self-consumption incentives and dynamic tariffs can enhance revenue generation by leveraging renewable energy shifts and load management. Similarly, subsidies for peak-shaving or frequency regulation, as noted by [59], could significantly improve profitability and revenue consistency, particularly in deregulated markets, by aligning financial incentives with grid stabilisation needs.

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

	Financial profits from TS3: bottleneck-controlled strategy								
	Quantiles $[\hat{q}_t^{\alpha}, \hat{q}_t^{1-\alpha}]$	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
Market	**Model**									
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 α	**€18,682**	€16,799	€17,613	€17,089	€16,571	€16,410	€13,524	€29,869	€16,670
BM	Average α	€6,398	€4,102	€5,731	**€7,582**	€7,376	€4,183	€26	€75,879	€5,057
DUAL	Average α	**€20,048**	€17,504	€19,390	€19,669	€18,668	€17,531	€13,466	€87,540	**€18,039**

6. Conclusion

This study explored the role of quantile-based trading strategies in optimising BESS profitability across the DAM and BM. By examining three strategies – TS1, TS2, and TS3 – and implementing a dual-market approach, TS3-Dual, we demonstrated the advantage of leveraging both markets to enhance returns. Among these, TS3-Dual proved the most effective, using flexible timestamp orders to balance the DAM's price stability with the BM's volatility, which facilitated higher profitability through increased trading frequency. Our findings emphasise the significance of strategic quantile pair selection, especially with high quantiles such as 0.7–0.9 in the BM, which captured extreme price values effectively. In the DAM, the baseline 0.5–0.5 quantile pair generally performed best, highlighting the stable nature of this market. Additionally, model choice impacted profitability, with RF and LGBM delivering the most reliable results due to their adaptability and forecasting accuracy. In terms of the economic viability of BESS trading, analysing cost implications, we demonstrate the potential for profitable engagement in energy markets with appropriate battery sizing and trading strategies. Future research could explore the incorporation of intra-day markets into trading strategies, delve into the price impact on BM trading, and investigate the utilisation of reinforcement learning techniques for trading (e.g., [60]). The promising results underscore the role of quantile forecasting and dual-market strategies in enhancing BESS profitability. Continued research and innovation in this domain could further amplify the success of BESS in the evolving energy landscape.

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.

Acknowledgements

This work was conducted with the financial support of Science Foundation Ireland under Grant Nos. 18/CRT/6223 and 12/RC/2289-P2 which are co-funded under the European Regional Development Fund.

Appendix

See Table 4.

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