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CASCADING MACHINE LEARNING FOR SUB-HOURLY BESS DISPATCH: PAVING THE WAY FOR HYBRID PV-STORAGE INTEGRATION

Summary

This paper presents a sequential forecasting and optimization framework for Battery Energy Storage Systems (BESS) in the Iberian electricity market. Utilizing a cascading Quantile LightGBM architecture, the model predicts Day-Ahead and Intraday price spreads, feeding a Mixed-Integer Linear Programming (MILP) engine constrained by Rainflow cycle counting. While historically validated on a 10 MW/40 MWh standalone asset (achieving a 79.3% capture rate), this study focuses on the 2025 transition to 15-minute market time units (MTU15). We demonstrate how sub-hourly volatility harvesting optimizes dispatch during periods of high solar penetration and negative price spikes. Finally, we establish the framework's adaptability for future hybrid PV-Storage plants, where integrating high-resolution solar forecasting is required to mitigate imbalances.

Keywords: Sub-hourly Dispatch, Hybrid PV-Storage, Machine Learning, MILP Optimization, Energy Arbitrage

Field of application for the findings: Hybrid PV-Storage dispatch, BESS valuation, Algorithmic trading

Addressed audience: Grid operators, renewable energy developers, quantitative analysts

1. Introduction

The European energy landscape is undergoing a structural transformation driven by the massive deployment of Variable Renewable Energy (VRE) sources. In the Iberian Peninsula, the rapid integration of solar photovoltaic capacity has fundamentally altered price formation dynamics. This variability introduces a systemic "Duck Curve" phenomenon, characterized by price compression during midday hours and extreme volatility during evening ramps. To mitigate these risks and secure grid stability, Battery Energy Storage Systems (BESS) have become critical flexibility assets [3].

While early research extensively covered Day-Ahead (DA) market arbitrage, the value pool is rapidly shifting towards Intraday Auctions (IDA). Furthermore, the structural harmonization with the European Single Intraday Coupling in 2025 introduced 15-minute resolution products (MTU15). This temporal shift renders traditional hourly forecasting models obsolete, as they inherently smooth out the high-frequency price dislocations caused by transient meteorological events. This paper presents a robust algorithmic trading framework designed to harvest this sub-hourly volatility, utilizing sequential machine learning and strict physical optimization.

2. Methodology: From Price Forecasting to MILP Dispatch

The valuation of a BESS in a sequential market is a complex stochastic control problem under uncertainty. Our approach decomposes this challenge into two distinct layers: a predictive engine to navigate market noise, and a deterministic optimization engine to manage physical constraints.

2.1 Cascading Machine Learning Architecture

The trading strategy operates across sequential market gates. Prior to the DA market closure (12:00 D-1), the model generates absolute price forecasts to establish a baseline schedule. However, predicting subsequent Intraday prices as absolute values leads to severe error propagation [4]. In operations, once the DA clearing prices are published and known, they serve as a deterministic baseline. To filter stochastic noise, we implemented a hierarchical "Cascading" architecture. Rather than forecasting absolute IDA prices, subsequent models focus exclusively on predicting the price differentials (spreads) between the known DA baseline and upcoming IDA sessions.

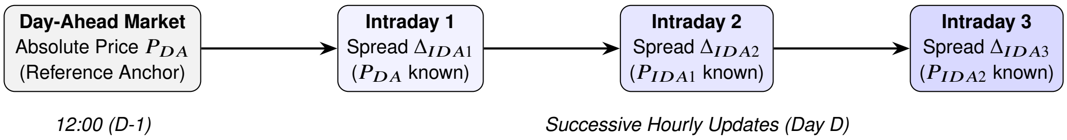

Fig. 1: Cascading Forecasting Timeline: From absolute baseline to iterative spread corrections.

Among evaluated architectures [1], a Quantile Regression based on LightGBM ($\tau = 0.5$) was selected. By minimizing the Pinball Loss to target the median, the algorithm is structurally robust to the extreme outliers.

2.2 MILP Optimization and Degradation Constraints

The forecasted price trajectories are fed into a Mixed-Integer Linear Programming (MILP) rolling-horizon optimizer. The objective function maximizes the net operational profit Π over the time horizon $\mathcal{T}$:

$$\max \Pi = \sum_{t \in \mathcal{T}} \left[\delta_{sell,t} \cdot (P_t - c_{trans}) - \delta_{buy,t} \cdot (P_t + c_{trans}) \right] \tag{1}$$

The physical state of the battery, represented by its energy level E_t (in MWh), is constrained by Kirchhoff's law for storage, adjusting for charge and discharge efficiencies (η_{ch}, η_{dis}):

$$E_t = E_{t-1} + \Delta t \cdot \left(p_{ch,t} \cdot \eta_{ch} - \frac{p_{dis,t}}{\eta_{dis}} \right) \quad \forall t \in \mathcal{T} \tag{2}$$

To ensure industrial viability, the model utilizes the Rainflow Counting algorithm [2] to impose a strict operational boundary limit. The energy throughput is constrained to approximately one equivalent full cycle per day, preserving a 15+ year asset lifespan.

3. Results: Harvesting Sub-Hourly Volatility

3.1 Historical Robustness (2021-2024)

The framework's robustness was validated over a 4-year backtest on the Spanish OMIE market. As summarized in Tab. 1, the Quantile LGBM strategy consistently outperformed linear baselines, capturing 79.3% of the theoretical Oracle value. Crucially, 56% of the total profit originated from Intraday adjustments. This operational performance translated into an IRR of 7.8% for a 10 MW/40 MWh standalone asset.

Tab. 1: Economic Benchmark of Predictive Architectures

Model Architecture	Capture Rate (%)	Intraday Contribution
Oracle (Perfect Foresight)	100.0%	61%
Quantile Regression (LGBM)	**79.3%**	**56%**
Neural Network (MLP)	79.0%	54%
Linear Baseline (Ridge)	51.2%	31%

3.2 *The MTU15 Multiplier*

The MTU15 resolution exposes deep, transient intra-hour price collapses driven by solar over-generation. Fig. 2 illustrates the response: rather than a continuous 60-minute charge, the MILP isolates the most negative 15-minute intervals. The strategy maintained a 78.9% capture rate despite the larger decision space.

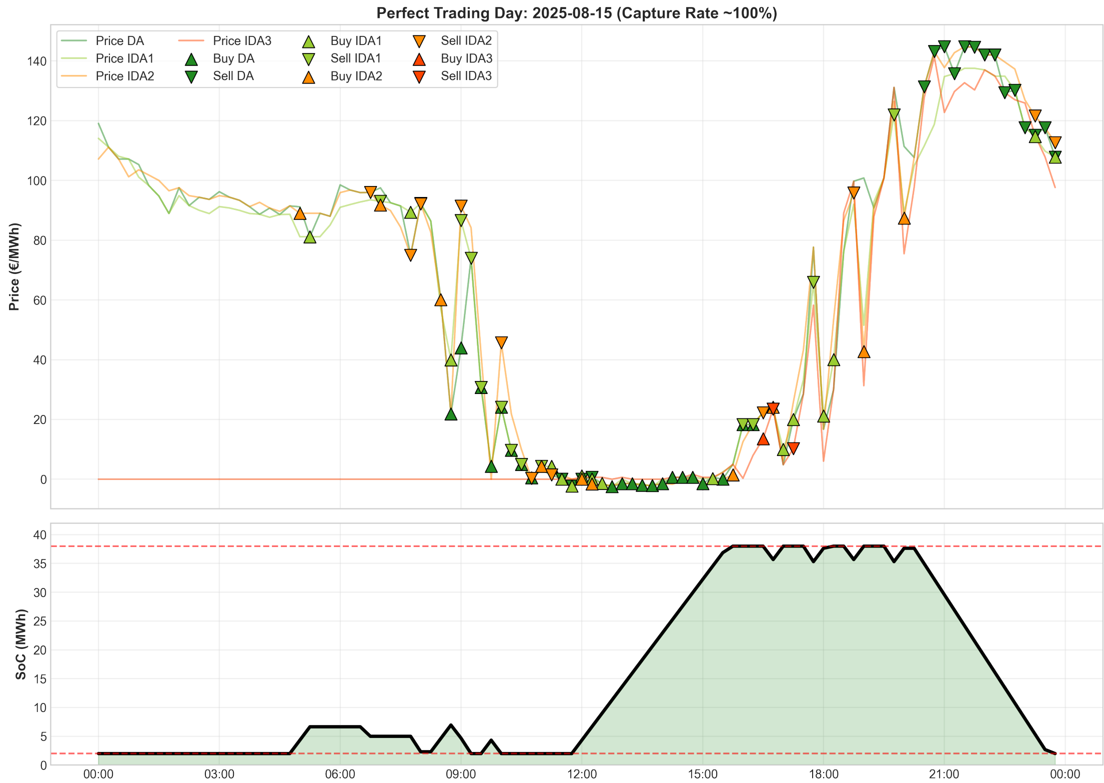

Fig. 2: MTU15 Volatility Harvesting: The optimizer isolates sub-hourly spikes for efficient arbitrage.

4. Future Work: End-to-End Pipeline and Market Expansion

While historically validated on standalone assets, the next logical evolution is its adaptation to co-located Hybrid PV-Storage plants. Future work will focus on developing a complete end-to-end algorithmic solution, linking high-resolution GHI forecasting with physical PV production modeling. This integrated pipeline will couple production directly with the price spread prediction engine to mitigate imbalance penalties. Finally, the scalability of this sub-hourly framework will be tested across diverse regulatory environments, notably high-growth markets such as India's power exchanges.

5. References

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