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Assessing the impact of price information on battery energy storage systems profitability: a rule-based dispatch analysis

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Abstract. Battery Energy Storage Systems (BESS) economic viability depends critically on accurate price forecasting for dispatch decisions. While existing literature extensively analyses BESS operation under perfect foresight, the impact of realistic forecast uncertainty remains insufficiently quantified. This paper develops a comprehensive framework to assess forecast-driven BESS operation using a rule-based dispatch model applied to three years of Iberian electricity market data (2020, 2022, 2024). By comparing forecast-driven operation against perfect foresight benchmarks, annual revenue losses of 17 to 25% attributable to forecast uncertainty are quantified. A critical asymmetry emerges charging decisions prove economically robust to temporal forecast errors, while discharge timing errors account for up to 68% of total revenue degradation in solar-dominated markets. Analysis reveals that market structure evolution, specifically persistent midday price floors, fundamentally alters forecast sensitivity patterns. Artificial noise injection demonstrates that 2024 market conditions exhibit resilience at 70% forecast accuracy, while 2020 conditions require 95% accuracy for comparable performance. These findings indicate that pre-feasibility assessments assuming perfect foresight systematically overestimate BESS revenues by 15 to 25%, with significant implications for investment decision-making.

Key words. Battery Energy Storage Systems, electricity price forecasting, revenue loss, energy arbitrage, techno-economic assessment.

1. Introduction

The global energy transition, driven by the urgent need to reduce greenhouse gas emissions, has fundamentally reshaped electricity systems worldwide [1, 2]. Renewable energy sources (RES), particularly solar photovoltaic and wind, now account for a growing share of installed generation capacity. While this shift is essential for decarbonisation, it introduces significant operational challenges: the intermittency and variability of RES create intraday price fluctuations and supply-demand imbalances that must be continuously managed [3, 4].

It is in this context that Battery Energy Storage Systems (BESS) have gained strategic importance. By decoupling electricity generation from consumption in time, BESS enable a wide range of applications: energy arbitrage, frequency regulation, peak shaving, and integration of distributed resources [5]. The global BESS market is projected to grow substantially over the coming decade, driven by falling costs, advances in lithium-ion technology, and expanding market participation frameworks [6, 7].

The economic viability of BESS depends critically on accurate electricity price forecasting. Unlike reactive generation assets, storage systems must commit to charging and discharging schedules hours in advance based on anticipated price trajectories. This forward-looking structure introduces fundamental exposure to forecast uncertainty: suboptimal scheduling driven by inaccurate predictions directly reduces arbitrage revenues and investment returns. Yet the majority of BESS techno-economic assessments still rely on backtesting approaches that assume perfect foresight of future prices [8], systematically overestimating realised revenues by assuming the operator knows in advance the optimal charge and discharge hours [9]. Empirical evidence illustrates this gap clearly: analysis of the Lake Bonney BESS in Australia showed that realised revenues in May 2023 reached only a fraction of the theoretical perfect foresight benchmark, with the gap attributed primarily to forecast-driven dispatch errors [9]. Despite such evidence, the literature lacks a systematic characterisation of forecast-induced revenue degradation across different market regimes, and a mechanistic explanation of which dispatch decisions are most sensitive to forecast errors.

This paper addresses this gap directly through a comprehensive analysis of forecast-driven BESS operation across three contrasting years of Iberian electricity market data: pandemic disruption (2020), an energy crisis (2022), and renewable-dominated conditions (2024). Forecast-driven operation is systematically compared against perfect foresight benchmarks to quantify revenue degradation, identify scheduling biases, and elucidate how market structure evolution alters the economic relevance of forecast accuracy.

2. Objectives of the work

This research pursues three complementary objectives:
(1) quantify forecast-induced revenue degradation across three contrasting market regimes (2020, 2022, 2024) by comparing forecast-driven operation against perfect foresight benchmarks; (2) decompose forecast impact across charging and discharging decisions through confusion matrices and revenue-loss attribution, revealing asymmetric sensitivities; and (3) elucidate how market structure evolution alters the economic relevance of forecast accuracy through normalised price distribution analysis and controlled noise injection experiments.

3. Methodology

A. BESS model and financial framework

The BESS is represented using the energy-based bucket model abstraction. In this formulation, the battery is treated as an energy reservoir with a given capacity E_{nom}, maximum charging power P_{ch}, maximum discharging power P_{dis}, and round-trip efficiency defined by one-way charging efficiency η_{ch} and discharging efficiency η_{dis}. The state of charge (SOC) evolves as:

$$SOC(t+1) = SOC(t) + P_{ch}(t) * \eta_{ch} - P_{dis}(t) / \eta_{dis}$$

subject to $SOC_{min} \leq SOC(t) \leq E_{nom}$, and $0 \leq P_{ch}(t) \leq P_{ch}(max)$, $0 \leq P_{dis}(t) \leq P_{dis}(max)$. The bucket model is well established for simplified techno-economic assessments as it captures the essential dynamics of energy storage without introducing unnecessary computational complexity.

The BESS case used throughout this study corresponds to a 10 MWh / 5 MW (2-hour duration) system with charging and discharging efficiencies of 0.92 each, a minimum SOC of 10%, and a capital expenditure of 350 EUR/kWh. These parameters are representative of utility-scale lithium-ion systems in the current market [12]. Economic viability is assessed via the 20-year net present value (NPV) using a 6% discount rate, which serves as the primary investment decision criterion due to its ability to capture both the magnitude and the temporal distribution of project cash flows.

B. Rule-based dispatch model

The dispatch framework is a rule-based (RB) model designed for pre-feasibility assessment. For each evaluation period (daily in this study), the model iterates over a finite set of candidate dispatch schedules defined by combinations of a charging start hour c and a discharging start hour d. For each pair (c, d), it simulates the SOC trajectory, computes the resulting revenue at market prices, and selects the schedule with the highest revenue:

$$(c^*, d^*) = argmax\ R(c, d, p_{real}), \quad (c, d)\ in\ W_{ch} \times W_{dis}$$

Charging is restricted to the window W_{ch} = {9:00, 10:00, 11:00, 12:00, 13:00, 14:00} and discharging to W_{dis} = {17:00, 18:00, 19:00, 20:00, 21:00, 22:00}, yielding 36 candidate combinations per day. These windows were derived from the frequency distributions of daily price minima and maxima observed in the Iberian market in 2024, where the lowest prices systematically occur during peak solar generation hours and the highest prices during the evening demand peak. The same windows are applied to 2020 and 2022 to ensure methodological consistency, though this introduces a known limitation for early-morning or late-evening arbitrage opportunities in those years.

Each charge or discharge block has a fixed duration of two hours. This constraint ensures that a full cycle can always be completed within the selected windows and aligns with the 2-hour duration of the BESS system under study. Revenue for a given schedule is computed as the sum of energy dispatched multiplied by the realised market price at each hour, accounting for round-trip efficiency losses.

C. Forecast evaluation framework

In standard pre-feasibility backtesting, the RB model selects the best schedule using realised prices, effectively assuming perfect foresight. To isolate the economic impact of forecast errors, a forecast-driven variant is implemented in which scheduling decisions are based on forecasted prices, but revenues are settled at realised prices. This separation allows the effect of forecast inaccuracy to be isolated from the underlying dispatch logic.

Three revenue concepts are formally defined:

$R_{PF} = R(pi(p_{real}, p_{real})$ *[Perfect foresight revenue]*

$R_{REAL} = R(pi(p_{fc}, p_{real})$ *[Forecast-realised revenue]*

$R_{EXP} = R(pi(p_{fc}, p_{fc})$ *[Forecast-expected revenue]*

where pi(.) denotes the schedule-selection rule of the RB model. R_{PF} provides the theoretical upper bound achievable under full information. R_{REAL} is the revenue actually earned when forecasted schedules are settled at market prices and is the only quantity observable in real operation. R_{EXP} is the revenue the operator anticipates at dispatch time and governs investment expectations.

Two complementary loss indicators are derived:

$$L_{rev} = R_{PF} - R_{REAL} \geq 0$$
[Revenue loss due to imperfect foresight]
$$L_{exp} = R_{EXP} - R_{REAL}$$
[Expectation loss: forecast bias indicator]

L_{rev} is always non-negative by construction, as the optimal perfect foresight schedule cannot be outperformed by any forecast-based schedule when settled at the same realised prices. L_{exp} may be positive (forecast optimism) or negative (forecast pessimism) and reveals the directional bias of the operator's revenue expectations at dispatch time.

D. Data and noise injection

Backtesting data consist of hourly day-ahead market prices from the Iberian electricity market (MIBEL) for 2020, 2022, and 2024. Commercial day-ahead price forecasts provided by the same external provider are used across all three years, ensuring consistency in forecast quality across market regimes. These three years were selected deliberately to represent structurally distinct market conditions: low-volatility pandemic-suppressed demand (2020), the European energy crisis driven by natural gas price shocks (2022), and solar-dominated renewable operation with persistent midday price floors (2024).
To complement the empirical forecast analysis and to disentangle the effect of forecast quality from market structure, a controlled noise injection procedure is applied. Gaussian noise with zero mean and varying standard deviation sigma is added to the realised price series:

$$p_{fc}(t) = p_{real}(t) + \varepsilon(t),$$
$$\varepsilon(t) \sim N(0, \sigma^2)$$

This generates synthetic forecast ensembles at systematically varied accuracy levels, each preserving the expected price level and spread while perturbing the intraday shape. For each value of sigma, multiple independent scenarios are generated using different random seeds. Forecast accuracy is quantified as a normalised RMSE metric:

$$Accuracy = 1 - RMSE(p_{real}, p_{fc}) / mean(p_{real})$$

bounded between zero and one, where unity corresponds to perfect foresight. For each synthetic forecast, the RB model selects a schedule based on forecasted prices, and the resulting revenue is evaluated at realised prices, yielding the normalised revenue ratio $k = R_{REAL} / R_{PF}$.

4. Results and discussion

A. Revenue analysis

Figure 2 presents the annual revenues and 20-year NPV for the three scenarios across all market years. Forecast uncertainty imposes a material economic penalty in all years, with the revenue losses summarised in Table 1.

Table 1. Revenue loss analysis across market years.

Year	R_{PF} [EUR]	R_{REAL} [EUR]	L_{rev} [EUR]	L_{exp} [EUR]	% Loss
2020	18 000	13 500	4 500	-500	25.0%
2022	172 100	142 000	30 100	+7 100	17.4%
2024	163 300	135 000	28 300	-7 600	17.3%

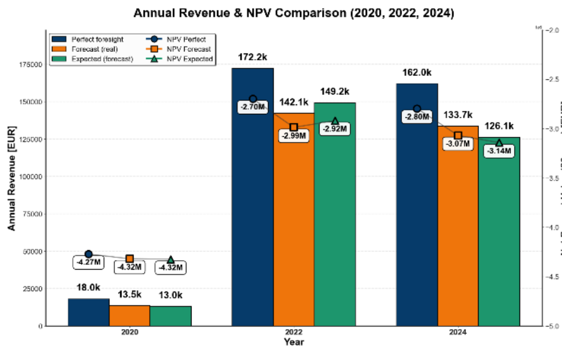


Fig.

Figure 2. Annual revenue and NPV comparison for each year, highlighting the differences between perfect foresight, forecast-realised, and forecast-expected scenarios.

The percentage revenue loss decreases from 25.0% in 2020 to approximately 17% in 2022 and 2024. This counter-intuitive reduction during high-volatility years reflects a structural effect: as price spreads widen, the distinction between charging and discharging periods becomes more pronounced, improving the model's ability to identify correct arbitrage windows despite forecast inaccuracies. In a flat-spread environment like 2020, even small temporal forecast errors can redirect energy allocation to the wrong side of a narrow arbitrage spread, causing disproportionate revenue loss.

The expectation loss reveals important directional asymmetry across years. In 2020 and 2024, forecasts were pessimistic, underestimating revenues by 500 EUR and 7 600 EUR respectively, suggesting that forecast-based operators would have been pleasantly surprised by outcomes. In 2022, forecasts exhibited significant optimism, overestimating revenues by 7 100 EUR, reflecting the exceptional unpredictability of the energy crisis.

Daily revenue loss distributions are right skewed in all three years, confirming that a small subset of extreme forecast events drives a disproportionate share of annual degradation. In 2022, the mean daily loss reaches 82 EUR with a 95th-percentile value (VaR95) of 329 EUR, reflecting the high-impact nature of forecast errors during the crisis. In 2024, the mean daily loss (77 EUR) and VaR95 (284 EUR) are somewhat lower, suggesting improved forecast robustness under the more structured solar-driven price regime.

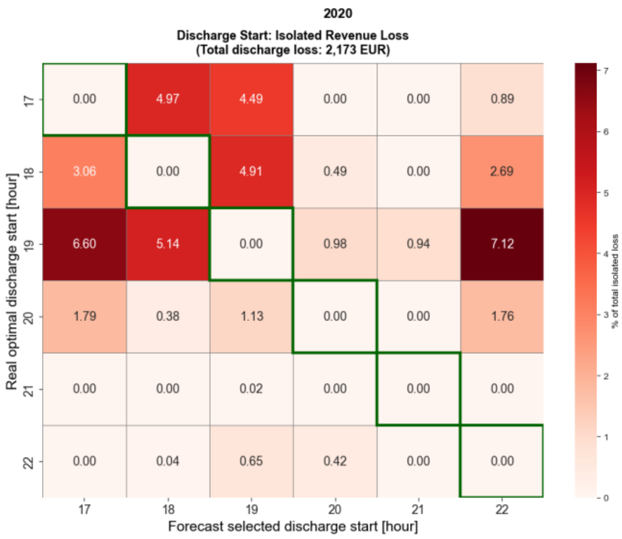
B. Scheduling patterns and bias

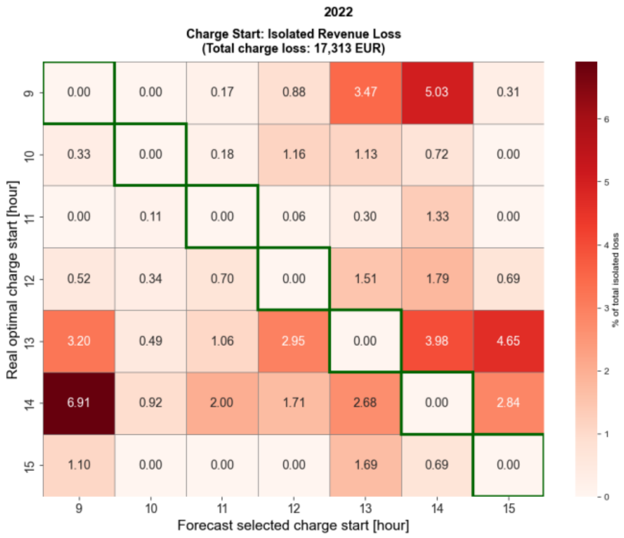
To diagnose the operational drivers of revenue degradation, revenue-loss matrices are constructed by weighting each mis-scheduling event by its isolated economic consequence. For each day and each decision type (charge or discharge), the matrix records the annual revenue loss attributable to selecting a given forecast hour when the realised optimal was a different hour, allowing a direct quantification of which timing errors are most costly.

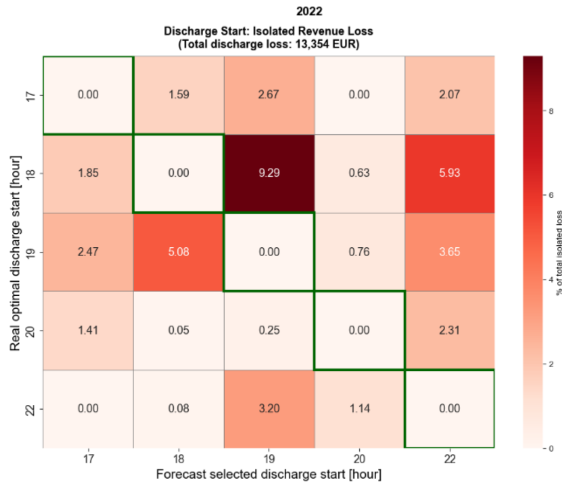
The revenue-loss matrices reveal a critical asymmetry across all three years. Charging mis-schedules contribute only marginally to total annual losses: because charging prices form wide, flat midday valleys, temporal misalignment across adjacent hours incurs low marginal cost regardless of which hour within the window is selected. Discharge timing errors, by contrast, are economically amplified by the narrowness and sharpness of evening price peaks, where missing the optimal hour by even one position can forfeit a large fraction of the available spread.

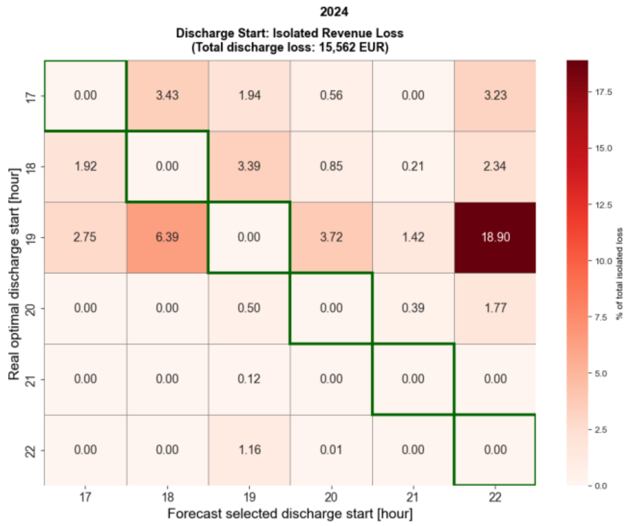
Figure 4 presents the revenue-loss matrices for 2020, 2022, and 2024.

The contrast between diffuse, low-value charging losses and concentrated, high-value discharging losses illustrates the asymmetric economic sensitivity of the two decision types.









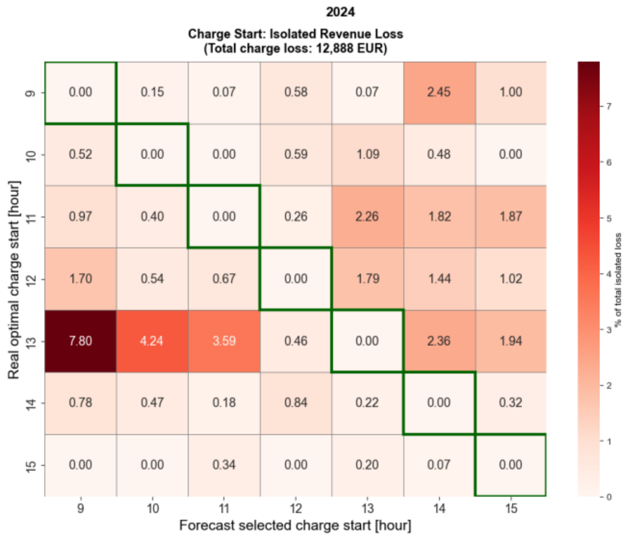


Fig. 4. Charge and discharge revenue-loss matrices for 2020, 2022, and 2024. Cell values represent the isolated annual revenue loss (EUR) attributable to each mis-scheduling event. The contrast between the diffuse, low-value charging losses and the concentrated, high-value discharging losses illustrates the asymmetric sensitivity.

Across all three years, discharge timing errors account for approximately 60 to 68% of total forecast-induced revenue degradation, despite forecast inaccuracies being symmetric across charging and discharging periods. This is the central empirical finding of this work: the economic impact of a forecast error depends not on when it occurs but on the price structure at that time. Errors during flat price segments are harmless; errors during sharp price spikes are costly. This finding challenges the conventional assumption that forecast improvements should target overall accuracy symmetrically, demonstrating instead that discharge peak localisation is the critical capability for BESS operators in renewable-dominated markets.

C. *Forecast accuracy and market structure*

Figure 5 presents the accuracy-revenue curves derived from the noise injection procedure for 2020, 2022, and 2024, relating normalised forecast accuracy to the ratio of achieved over perfect foresight revenue.

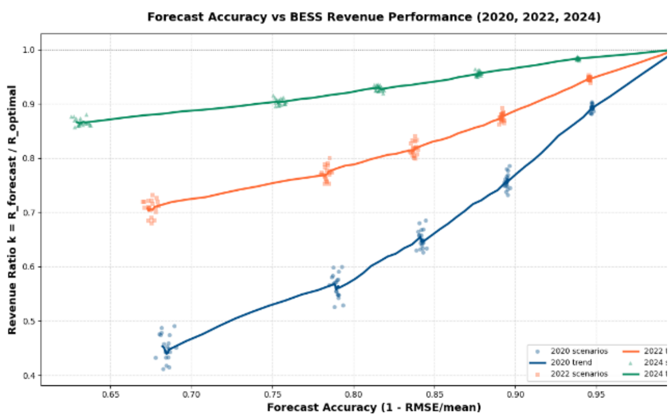


Fig. 5. Relationship between forecast accuracy and relative BESS revenue performance for 2020, 2022, and 2024, based on artificial forecast scenarios. Each point corresponds to one synthetic scenario; trend lines highlight the year-specific accuracy-revenue relationship.

The curves reveal a strongly non-stationary relationship between forecast quality and economic value. In 2020, revenue performance degrades sharply with decreasing accuracy: achieving 90% of perfect foresight revenue requires approximately 95% forecast accuracy. In 2022, the sensitivity is reduced but remains significant. In 2024, the relationship is markedly flatter: a forecast with 90% accuracy captures approximately 96% of optimal revenues, and even 70% accuracy still reaches approximately 89%.

The mechanistic explanation lies in the structural evolution of Iberian intraday price formation. Figure 6 presents normalised hourly price distributions for 2020 and 2024, allowing a direct comparison of the intraday price shape independently of absolute price levels.

In 2020, charging-window prices remain elevated and dispersed (average normalised standard deviation: 0.113), so forecast errors on the charging side can displace energy allocation to suboptimal hours with material revenue consequences. In 2024, the midday price floor collapses toward zero under persistent solar over-generation (average std: 0.059), rendering precise charging timing nearly irrelevant: any hour within the low-price plateau produces similar economic outcomes.

The discharge window, by contrast, maintains sharp evening peaks in 2024 (average std: 0.216), meaning even small temporal forecast errors around the discharge peak translate into significant revenue losses. This structural asymmetry explains both the flatter accuracy-revenue curve in 2024 and the continued dominance of discharge timing errors in total revenue degradation.

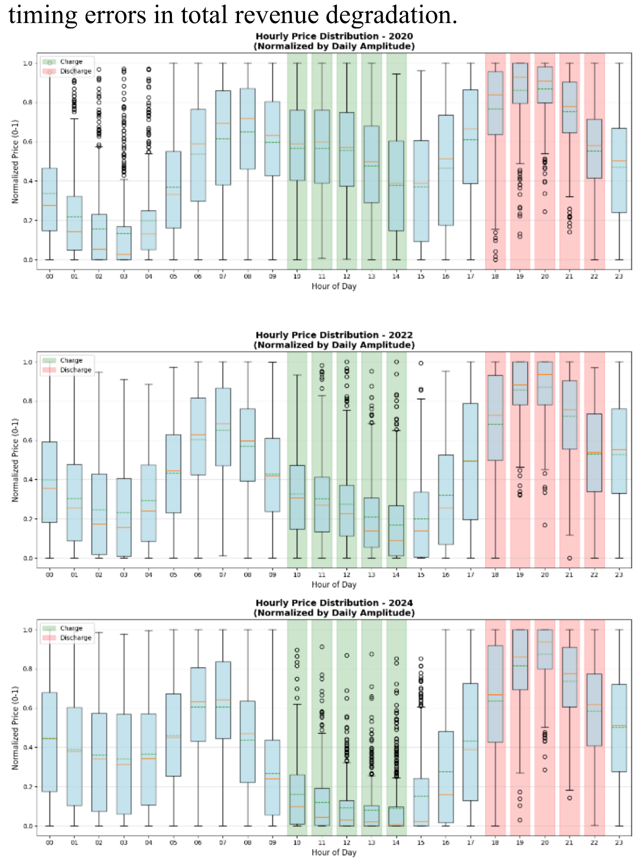


Fig. 6. Boxplot representation of normalised hourly electricity price curves for 2020 (left) and 2024 (right). Prices are

normalised by daily amplitude. Green shaded areas: charging window (09:00 to 14:00); red shaded areas: discharging window (18:00 to 22:00).

These findings carry important practical implications. Pre-feasibility assessments based on perfect foresight backtesting systematically overestimate BESS revenues by 17 to 25%, and sensitivity analyses cannot assume a single fixed accuracy-revenue relationship: the same forecast quality produces fundamentally different economic outcomes depending on the prevailing market structure. From a forecast procurement perspective, specialised capabilities in discharge peak localisation increasingly justify premium pricing as markets transition toward solar dominance, while improvements in charging-side accuracy deliver diminishing marginal returns.

5. Conclusions

This paper has developed a rigorous framework to assess the economic impact of price forecast uncertainty on BESS dispatch using three years of Iberian electricity market data. The analysis yields three principal conclusions with direct relevance for investment decision-making and forecasts procurement.

First, forecast-induced revenue losses of 17 to 25% relative to perfect foresight benchmarks are quantified across contrasting market regimes. These results demonstrate that the standard industry practice of perfect foresight backtesting systematically overstates achievable revenues, with direct implications for NPV projections, debt sizing, and investment viability thresholds.

Second, a critical asymmetry is identified: discharge timing errors account for 60 to 68% of total forecast-induced revenue degradation, despite forecast inaccuracies being symmetric across charging and discharging periods. This arises because charging occurs during wide, flat price valleys where timing errors have low marginal cost, while discharging targets narrow, sharp peaks where a single misplaced hour can eliminate most of the arbitrage value. Forecast improvement strategies should therefore prioritise discharge peak localisation rather than overall accuracy.

Third, a non-stationary relationship between forecast accuracy and economic value is demonstrated across market years. The accuracy threshold required to capture 90% of perfect foresight revenue has shifted from approximately 95% in 2020 to approximately 70% in 2024, driven by solar-induced midday price floor formation that decouples charging decisions from forecast quality. Investment sensitivity analyses must account explicitly for this evolving structure rather than assuming fixed accuracy-revenue relationships.

Taken together, these results indicate that robust BESS investment assessment in renewable-dominated markets requires: (i) explicit correction of perfect foresight revenue estimates by a market-regime-dependent factor of 17 to 25%; (ii) asymmetric sensitivity analysis that separates charging and discharging forecast contributions; and (iii) market-structure-aware accuracy-revenue models rather than static correction factors.

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