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Optimizing battery energy storage systems simplified dispatch: comparative analysis of temporal resolution, complexity and multi-market participation strategies

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Abstract. Battery Energy Storage Systems (BESS) investment decisions rely critically on revenue projections derived from operational models that vary significantly in complexity and temporal resolution. This paper systematically compares rule-based and linear programming dispatch formulations across different optimisation frequencies (daily, weekly, monthly) and market participation strategies (day-ahead only, day-ahead plus intraday, full cross-market including automatic frequency restoration reserve) using three years of Iberian electricity market data. Results demonstrate that temporal granularity materially affects revenue estimates, with coarse optimisation causing losses of 3.5 to 14.0% relative to daily resolution. Dispatch complexity analysis reveals that linear programming achieves revenue uplifts of 4.6 to 5.5% compared to rule-based approaches for single-market operation. However, market participation scope dominates both effects: exclusive day-ahead arbitrage yields negative NPV across all years, while multi-market participation including aFRR produces positive NPV, with ancillary services contributing 75 to 85% of total revenues. These findings demonstrate that pre-feasibility assessments based on simplified models and energy-only participation systematically underestimate both achievable revenues and required operational sophistication for economic viability.

Key words. Battery Energy Storage Systems, optimisation models, multi-market participation, ancillary services, revenue stacking.

1. Introduction

The accelerating deployment of Battery Energy Storage Systems in electricity markets worldwide has created strong demand for robust techno-economic assessment methodologies. With individual projects representing capital expenditures in the range of tens of millions of euros, investment decisions depend critically on revenue projections derived from operational models. Yet these models vary enormously in their complexity, temporal resolution, and scope of market participation, and the differences in projected revenues can be large enough to determine whether a project appears viable or not.

The Iberian electricity market has undergone particularly rapid structural change in recent years. Solar photovoltaic capacity more than doubled between 2020 and 2024, reaching over 30 GW in Portugal and Spain combined, and renewable sources now account for more than 60% of generation [1, 2]. This transformation has produced a characteristic intraday price shape: persistent midday price depressions driven by solar over-generation, followed by sharp evening peaks as solar output falls and demand peaks. This evolving price structure directly affects the relative importance of different modelling choices, as dispatch strategies optimised under one market regime may perform poorly under another.

Current BESS feasibility assessments exhibit significant heterogeneity. Industry studies often use simplified rule-based heuristics optimised over extended horizons, focusing on day-ahead energy arbitrage to maximise transparency and minimise data requirements [3]. Academic research, by contrast, typically employs sophisticated optimisation frameworks incorporating multiple revenue streams including ancillary services [4, 5]. The appropriate balance between accuracy, computational tractability, and stakeholder interpretability remains unclear, and there is no systematic empirical basis for choosing between these approaches in a given context.

This fragmentation poses a direct practical problem: a preliminary study using monthly rule-based optimisation may yield revenues differing substantially from a detailed daily linear programming analysis, but without systematic comparison stakeholders cannot determine whether these differences reflect genuine operational value or modelling artefacts. The same uncertainty applies to market participation scope: the literature suggests that energy arbitrage alone may be insufficient for economic viability, but quantitative comparisons across participation strategies under consistent model and data conditions are scarce.

This paper addresses these gaps through a systematic empirical comparison using three years of Iberian electricity market data spanning contrasting structural regimes. By isolating the impacts of temporal resolution, dispatch complexity, and market scope, it provides empirical guidance for matching modelling sophistication to assessment context and decision needs.

2. Objectives of the work

This research pursues four interconnected objectives: (1) quantify the revenue impact of temporal resolution by comparing daily, weekly, and monthly optimisation frequencies across 2020, 2022, and 2024; (2) benchmark rule-based versus LP dispatch formulations to determine the revenue uplift achievable through increased sophistication; (3) assess multi-market participation strategies by comparing energy-only operation against full cross-market optimisation including aFRR; and (4) provide model selection guidance through a qualitative comparison of formulations across transparency, scalability, and suitability for different assessment stages.

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 [7].

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 [6]. 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:

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

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. Linear programming model

The linear programming (LP) model determines optimal dispatch and market participation by solving a constrained optimisation over the full daily horizon under perfect foresight. The objective is to maximise total revenue across three components:

$$\max \Pi = \Pi_{energy} + \Pi_{aFRR,cap} + \Pi_{aFRR,act} \quad (1)$$

Energy arbitrage revenues Π_{energy} are obtained from buying and selling electricity in the day-ahead (DA) and intraday (IDA) markets. aFRR revenues comprise capacity remuneration $\Pi_{aFRR,cap}$ for reserve availability (EUR/MW/h) and energy remuneration $\Pi_{aFRR,act}$ for activations (EUR/MWh), sourced from REN [8, 9].

Physical constraints enforce SOC bounds (SOC_min to SOC_max), power limits (0 to P_max), and a cycling constraint limiting daily throughput to N_cycle times nominal capacity.

Market coupling constraints ensure that DA, IDA, and reserve activation energy sums equal physical charge and discharge at each hour. The aFRR reserve offered is bounded by the power rating R_max. The LP is solved using Gurobi [10].

D. Market configurations and data sources

Four participation configurations are analysed: (1) DA only; (2) DA + IDA; (3) aFRR only; (4) DA + IDA + aFRR. The simulated BESS has a nominal energy capacity of 10 MWh, a power rating of 5 MW, a round-trip efficiency of 84.6% (eta_c = eta_d = 0.92), a minimum SOC of 10%, and a capital expenditure of 350 EUR/kWh [6]. Financial viability is assessed via a 25-year NPV with a 6% discount rate.

Backtesting covers three market years: 2020 (low-volatility, pandemic suppression), 2022 (extreme volatility, European energy crisis), and 2024 (solar-dominated, persistent midday over-generation). Day-ahead and intraday prices are sourced from MIBEL/OMIE [11]. aFRR capacity prices, activation prices, and activated volumes are sourced from REN [12, 13, 14].

4. Results and discussion

A. Impact of temporal resolution

Figure 1 presents total annual revenues under daily, weekly, and monthly optimisation. Revenues consistently decrease with coarser granularity, confirming that temporal resolution materially affects revenue estimates. Table 1 summarises the revenue losses.

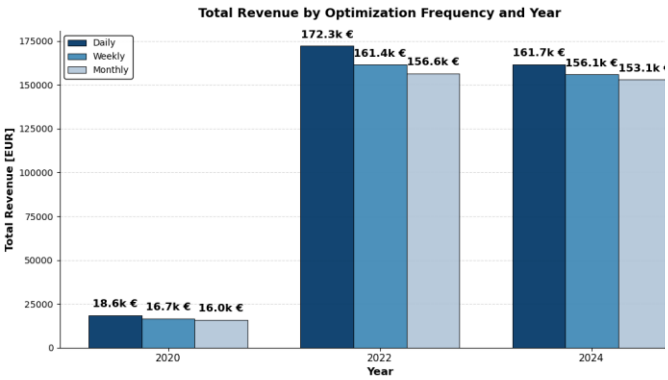

Fig. 1. Total annual revenue obtained under daily, weekly, and monthly optimisation frequencies for 2020, 2022, and 2024.

Table 1. Revenue losses from reduced optimisation granularity, relative to daily optimisation.

Year	Weekly vs daily (%)	Monthly vs daily (%)
2020	-10.2%	-14.0%
2022	-6.3%	-9.1%
2024	-3.5%	-5.3%

The impact of granularity is strongly correlated with market volatility. In low-volatility 2020, monthly optimisation sacrifices 14.0% of potential revenue, while in the more structured 2024 conditions the penalty reduces to 5.3%. Coarser optimisation converges toward a limited set of dominant schedules that are adequate during stable solar-driven price conditions but miss isolated high-value opportunities during volatile periods.

Seasonal analysis (Fig. 2) reveals that losses concentrate in high-volatility months: September to December 2020 and summer 2022 show differences reaching up to 10 EUR/day in 2020 and 80 EUR/day in 2022. Months dominated by consistent solar-driven price patterns show minimal sensitivity to optimisation frequency, suggesting that adaptive granularity strategies could reduce modelling effort without sacrificing accuracy.

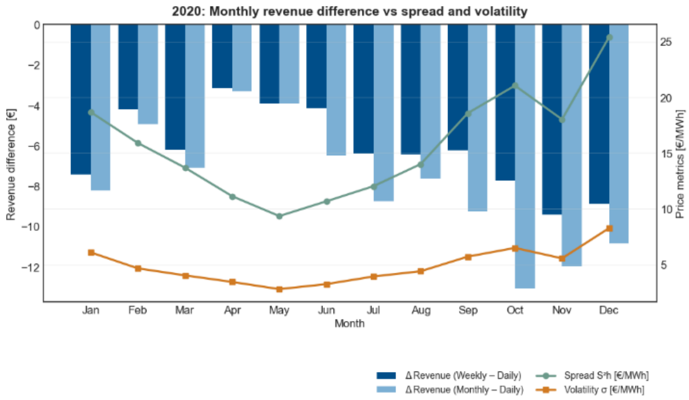

Fig. 2. Monthly average revenue difference between coarse and daily optimisation for 2020 (left), 2022 (centre), and 2024 (right). Granularity effects concentrate in high-volatility months.

B. Dispatch complexity: rule-based versus linear programming

Table 2 compares annual day-ahead revenues obtained with the RB and LP formulations. The LP consistently outperforms the RB model, with revenue uplifts of 3.5 to 5.5%. The uplift magnitude is remarkably stable across years despite dramatically different absolute revenue levels, suggesting a structural characteristic of the RB model rather than a market-specific effect.

Table 2. Rule-based versus LP annual day-ahead revenues and revenue uplift.

Year	RB revenue [EUR]	LP revenue [EUR]	Uplift [%]
2020	33 830	35 372	4.6%
2022	197 664	208 492	5.5%
2024	168 567	174 528	3.5%

LP gains arise from three mechanisms: (i) partial cycling exploiting secondary intraday price peaks unavailable to full-cycle-only rules; (ii) precise discharge timing within narrow price spike windows; and (iii) temporal load shifting positioning SOC strategically for subsequent periods. The modest uplift (under 6%) suggests that for early-stage screening focused solely on energy arbitrage, rule-based models provide reasonable accuracy while offering advantages in transparency and interpretability. Computationally, the LP requires approximately 31.5 seconds versus 2.1 seconds for the RB model for a full year of hourly data, a difference modest enough not to justify preferring the simpler formulation on grounds of runtime alone. Fig. 3 illustrates the annual revenue and corresponding NPV comparison between both formulations.

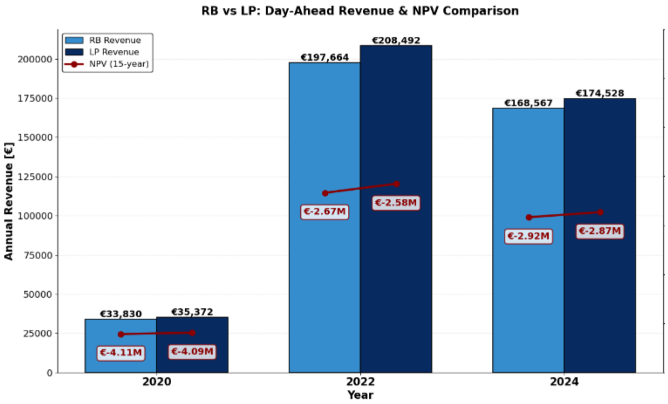

Fig. 3. Comparison of annual day-ahead revenues and corresponding NPV for rule-based and LP dispatch formulations across 2020, 2022, and 2024. The LP consistently outperforms the rule-based model with a revenue uplift stable between 3.5 and 5.5% across all three years, irrespective of absolute revenue level.

The stability of the LP uplift across years despite dramatic differences in absolute revenues (from 18k EUR in 2020 to 208k EUR in 2022) further suggests that the 4 to 6% gap is an intrinsic property of the constraint structure of the rule-based formulation rather than a market condition effect. The RB model is structurally unable to perform partial cycles or intertemporally coordinate charge and discharge across multiple price peaks, while the LP exploits these opportunities as soon as they appear in the price signal, regardless of the overall price level.

C. Market participation scope

Fig. 4 presents annual revenues disaggregated by revenue stream. While temporal resolution and dispatch complexity affect revenues by 3 to 14% and 4 to 6% respectively, market participation strategy determines whether the project is viable at all.

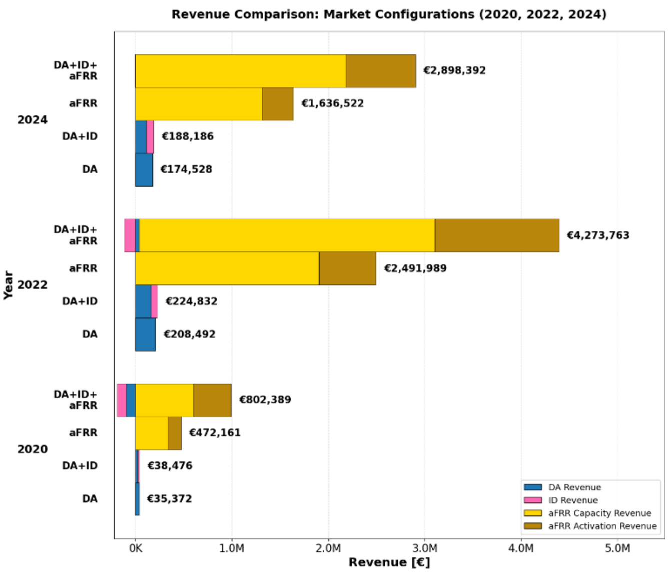

Fig. 4. Annual BESS revenue comparison across market participation configurations for 2020, 2022, and 2024, disaggregated by day-ahead, intraday, and aFRR revenue components.

Table 3. 25-year NPV by market participation configuration and year.

Configuration	2020 NPV [EUR]	2022 NPV [EUR]	2024 NPV [EUR]
DA only (LP)	-4.43M	-2.86M	-2.96M
DA + IDA (LP)	-4.27M	-2.70M	-2.86M
aFRR only (LP)	+0.09M	+2.71M	+1.47M
DA + IDA + aFRR (LP)	+1.02M	+5.89M	+3.92M

Exclusive day-ahead energy arbitrage yields negative NPV in all three years, even under optimal LP dispatch with daily resolution. Adding intraday trading provides marginal improvement but does not overcome this structural limitation. Participation in aFRR alone fundamentally alters the revenue profile: even in the low-revenue 2020 year, single-market aFRR participation produces near-breakeven NPV (+0.09M EUR), with capacity remuneration representing the dominant component. In 2022, aFRR-only NPV reaches +2.71M EUR. This result is particularly notable because aFRR operation is characterised by limited cycling: the BESS maintains an intermediate SOC to maximise reserve availability for both upward and downward activation, implying reduced degradation costs relative to energy arbitrage.

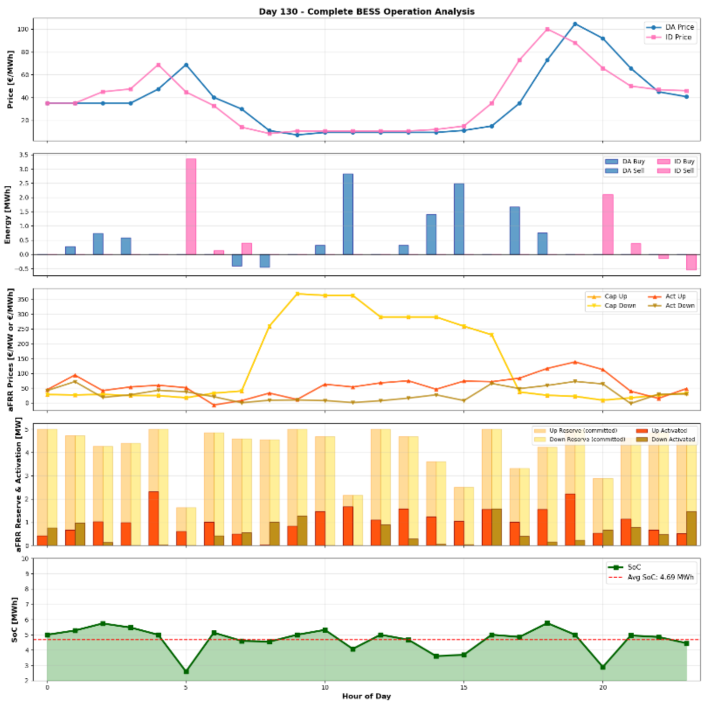

Fig. 5. Twenty-five-year NPV across market participation configurations for 2020, 2022, and 2024. Exclusive day-ahead operation yields negative NPV in all years. Only configurations including aFRR generate positive outcomes, with full cross-market optimisation (DA + IDA + aFRR) achieving the highest NPV across all three market regimes.

Full cross-market optimisation achieves strongly positive NPV across all years: +1.02M EUR in 2020, +5.89M EUR in 2022, and +3.92M EUR in 2024, with ancillary services contributing 75 to 85% of total revenues. In this configuration, the LP uses energy market transactions primarily for SOC management, as evidenced by negative DA and IDA revenues in some years reflecting the acceptance of energy costs in exchange for sustained reserve availability. The NPV outcomes across all configurations and years are summarised in Fig. 5.

This hierarchical importance, market scope far outweighing dispatch complexity and temporal resolution, carries critical implications for investment assessment. Resources devoted to refining optimisation algorithms deliver marginal returns if the business model assumes energy-only participation. Conversely, even simplified models incorporating realistic multi-market revenue streams provide more accurate investment guidance than sophisticated optimisation limited to energy arbitrage.

From a model selection perspective, these results suggest a clear hierarchy of priorities for investment assessment. At the screening stage, a simplified rule-based model with multi-market participation (including at minimum aFRR capacity revenues) provides far more decision-relevant information than a sophisticated LP model limited to energy arbitrage. At the feasibility stage, LP formulations become valuable for optimising market participation strategies and quantifying the marginal contribution of each revenue stream. At the operational planning stage, full cross-market LP optimisation with high temporal resolution is necessary to identify the precise scheduling decisions that maximise value under daily market conditions. This progression from simple to complex modelling should be matched to the decision stage rather than applied uniformly.

5. Conclusions

This paper has provided the first systematic empirical comparison of BESS dispatch modelling choices across temporal resolution, dispatch complexity, and market participation scope using three years of contrasting Iberian electricity market data. Three principal conclusions emerge.

First, temporal granularity materially affects revenue estimates, with monthly optimisation causing losses of 3.5 to 14.0% relative to daily resolution. Losses are strongly correlated with market volatility and concentrate in high-volatility months, suggesting that adaptive granularity strategies could substantially reduce modelling effort without sacrificing accuracy.

Second, linear programming achieves a consistent revenue uplift of 4.6 to 5.5% over rule-based approaches for day-ahead participation, remarkably stable across years. For early-stage screening, rule-based models offer a reasonable approximation while being substantially more transparent and interpretable.

Third, and most critically, market participation scope dominates both effects. Exclusive day-ahead arbitrage yields negative NPV in all years, while multi-market participation including aFRR produces strongly positive NPV with ancillary services contributing 75 to 85% of revenues. Investment assessments should prioritise getting the participation scope right before refining modelling sophistication.

Taken together, these results provide a practical decision framework: use rule-based models for initial screening with realistic multi-market scope, LP formulations when cross-market optimisation is required, and daily resolution during volatile market periods. Future work should extend this comparison to stochastic optimisation frameworks and to markets with different ancillary service structures, validating whether the observed hierarchical importance generalises beyond the Iberian context.

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