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A framework for assessing and modeling the market potential for battery energy storage systems in Southern Europe

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THESIS TITLE: A framework to assess and model the market potential for BESS in Spain.

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Collaborating Entity: Centrica Energy

PROJECT SUMMARY

A methodological framework has been developed and validated to assess the market potential of battery energy storage systems (BESS) in Spain, analyzing their participation in the Automatic Frequency Restoration Reserve (aFRR) market and in the Day-Ahead Market.
In the aFRR market, a backtest was conducted to establish a benchmark against a deterministic strategy. This analysis enabled a comparison of heuristic and adaptive strategies, assessing both their effectiveness and operability through economic parameters (revenues) and technical parameters (cycles per day). Additionally, a sensitivity analysis was performed to evaluate the model's robustness to variations in key parameters, and the regulatory and economic implications for BESS adoption in the Spanish power system are discussed.

A regression analysis over the past six years was carried out to identify the most relevant revenue drivers in the Day-Ahead market. The model's revenues were calculated using the characteristics of a representative battery provided by Centrica and Day-Ahead market prices. Variables such as generation from different technologies, installed capacity, and gas operating costs were also analyzed.

Keywords: BESS, aFRR, Day-Ahead, arbitrage, energy storage, Spain, grid flexibility, capacity reserve, demand-side management, energy optimization, price curves, market volatility, optimization algorithms, stochastic models, renewables integration, dynamic pricing, power balancing, battery longevity, cost–benefit analysis, electricity regulation

Results

In aFRR, energy-only strategies capture approximately 70% of the revenue of the deterministic benchmark while reducing cycles per day. Capacity-based strategies capture only around 30
The sensitivity analysis demonstrates that, across all strategies, a larger battery capacity significantly increases flexibility in energy auctions.

Strategy	Annual Revenue (EUR/MW-year)	Avg. Cycles/Day
Deterministic benchmark (energy only)	270,064	4.18
Deterministic benchmark (energy + capacity)	646,752	5.34
Energy-only participation (no premium)	177,812	4.70
Energy-only participation (best premium 94/37)	190,464	2.04
Constant capacity best case $p = 1\,\mathrm{MW}$	219,084	3.00
Best constant capacity and premiums in previous 3 days	223,596	2.10
Best previous capacity shape	219,596	2.95

Table 1: Summary of annual revenues and operational metrics by trading strategy in the aFRR market (2 h battery).

In the Day-Ahead market, gas operating cost was the main revenue driver before 2022 and after 2024, while its effect was neutralized in 2022 and 2023 due to the gas price cap.

Breaking down by seasons, we observe:
Spring: Onshore wind capacity is the strongest positive driver (due to high winds in April), while hydro capacity carries a small negative coefficient, indicating that spring runoff smooths price swings.
Summer: Solar share leads as the main positive driver—midday spreads peak under intense sun—whereas abundant hydro and wind generation dampen those spreads, reflected in their negative coefficients.
Autumn and Winter: Hydro capacity has a pronounced negative effect on spreads (thanks to autumn–winter inflows), while renewables share remains a positive driver because low solar and variable wind extend and deepen peak spreads.

Conclusions

In conclusion, the developed methodological framework has proven to be a robust tool for assessing the market potential of BESS in Spain. It enables comparison of different participation strategies in aFRR—evaluating revenues and cycles per day—and identification of key revenue drivers in the Day-Ahead market through regression analysis. The aFRR backtest validated that adaptive strategies can capture up to 70% of the deterministic benchmark, and the sensitivity analysis confirmed that increased battery capacity significantly enhances operational flexibility. Meanwhile, the Day-Ahead regression study revealed the critical role of gas operating cost in different periods and the impact of seasonal variables (wind, solar, and hydro) on price dynamics. Together, these findings provide a comprehensive view of the opportunities and limitations of energy storage systems, offering practical recommendations to optimize BESS operation and inform future regulatory and investment decisions.

TÍTULO DEL TFG: Marco metodológico para evaluar y modelar el potencial de mercado de sistemas de almacenamiento de energía con baterías (BESS) en España.

Autor: Marta Mencía Aguado
Director: Renaud Bruneliere, Haris Ziras
Entidad Colaboradora: Centrica Energy

RESUMEN DEL PROYECTO

Se ha desarrollado y validado un marco metodológico para evaluar el potencial de mercado de sistemas de almacenamiento de energía con baterías (BESS) en España, analizando su participación en el Mercado de Reserva Automática de Frecuencia (aFRR) y en el Mercado Diario (Day-Ahead).

En el caso de aFRR, se ha realizado un backtest con el objetivo de establecer un benchmark frente a una estrategia determinista. Este análisis ha permitido comparar las estrategias heurísticas y adaptativas, evaluando tanto su eficacia como su operatividad mediante parámetros económicos (ingresos) y técnicos (ciclos diarios). Además, se realizó un análisis de sensibilidad para evaluar la robustez del modelo ante variaciones de los parámetros clave y se discuten las implicaciones regulatorias y económicas para la adopción de BESS en el sistema eléctrico español

Se ha llevado a cabo un análisis de regresión con datos de los últimos seis años para identificar los impulsores de ingresos más relevantes. Asimismo, se examinó detalladamente cómo varía la influencia de dichos factores según las distintas estaciones del año y los meses. Los ingresos del modelo se calcularon utilizando las características de una batería representativa proporcionada por Centrica y los precios del mercado Day-Ahead. Además, se analizaron variables como la producción de las diferentes tecnologías de generación, la capacidad instalada y los costes operativos de gas, entre otros.

Palabras clave: BESS, aFRR, Day-Ahead, arbitraje, almacenamiento energético, España, flexibilidad de la red, reserva de potencia, gestión de la demanda, optimización energética, curvas de precios, volatilidad de mercado, algoritmos de optimización, modelos estocásticos, integración de renovables, tarificación dinámica, balance de potencia, durabilidad de baterías, análisis coste-beneficio, regulación eléctrica

Resultados

En aFRR, las estrategias de energía capturan aproximadamente el 70 % de los ingresos de la estrategia determinista, reduciendo al mismo tiempo los ciclos diarios. Por su parte, las estrategias basadas en capacidad apenas alcanzan alrededor del 30 % del ingreso determinista y también limitan el número de ciclos por día.

El análisis de sensibilidad muestra que, en todas las estrategias, disponer de una batería de mayor capacidad incrementa la flexibilidad en las subastas de energía.

Strategy	Annual Revenue (EUR/MW-year)	Avg. Cycles/Day
Deterministic benchmark (energy only)	270,064	4.18
Deterministic benchmark (energy + capacity)	646,752	5.34
Energy-only participation (no premium)	177,812	4.70
Energy-only participation (best premium 94/37)	190,464	2.04
Constant Capacity best case p=1MW	219,084	3.00
Best Constant Capacity and Premiums in the previous 3 days	223,596	2.10
Best Previous Capacity Shape	219,596	2.95

Table 2: Summary of annual revenues and operational metrics by trading strategy in the aFRR market (2h Battery).

En el mercado Day-Ahead, el coste de funcionamiento del gas (gas running cost) fue el principal impulsor de ingresos antes de 2022 y a partir de 2024, mientras que durante 2022 y 2023 su efecto quedó neutralizado por el tope en el precio del gas.

Al desglosar por estaciones, observamos:

Primavera: La capacidad eólica terrestre es el impulsor positivo más fuerte (debido a los vientos elevados de abril), mientras que la capacidad hidroeléctrica muestra un pequeño coeficiente negativo, lo que indica que el deshielo primaveral atenúa las variaciones de precios.

Verano: La proporción de energía solar lidera como impulsor positivo —las diferencias de precio alcanzan su punto máximo al mediodía por el intenso sol—, mientras que la abundancia de generación hidroeléctrica y eólica reduce esos diferenciales, reflejándose en sus coeficientes negativos.

Otoño e Invierno: La capacidad hidroeléctrica ejerce un fuerte efecto negativo sobre los diferenciales (gracias al aporte de lluvias y escorrentías otoño-invernales), mientras que la cuota de renovables permanece como impulsor positivo, ya que la baja generación solar y la variabilidad eólica extienden y acentúan los picos de precio.

Conclusiones

Como conclusión, el marco metodológico desarrollado ha demostrado ser una herramienta robusta para evaluar el potencial de mercado de los BESS en España, permitiendo comparar distintas estrategias de participación en aFRR —y sus resultados en ingresos y ciclos diarios—, así como identificar mediante regresión los principales impulsores de ingresos en el mercado Day-Ahead. El backtest en aFRR validó que las estrategias adaptativas pueden capturar hasta el 70% del benchmark determinista, mientras que el análisis de sensibilidad confirmó que aumentar la capacidad de la batería mejora significativamente la flexibilidad operativa. Por otra parte, el estudio de regresión para Day-Ahead reveló el papel clave del coste del gas en diferentes períodos y de las variables estacionales (eólica, solar e hidroeléctrica) en la dinámica de precios. En conjunto, estos resultados ofrecen una visión integral de las oportunidades y limitaciones de los sistemas de almacenamiento, aportando recomendaciones prácticas para optimizar la operación de BESS y guiar futuras decisiones regulatorias y de inversión.

1 Introduction

The expansion and integration of renewable energies replacing fossil fuels is one of the measures of the framework designed to achieve climate neutrality and amend Regulations (EC) No 401/2009 and (EU) 2018/1999 ("European Climate Law"), drafted by the European Parliament and the European Council with the support of EU stakeholders and policymakers.[1].

This framework aligns with "The Green Deal" of the European Commission, which includes a series of proposals aimed at EU climate, energy, transport, and tax policies to reduce net greenhouse gas emissions by at least 55% by 2030 compared to 1990 levels [2]. The REPowerEU Plan from the European Commission is accelerating the green transition and promoting massive investment in renewable energy [3]. Since November 2023, the Renewable Energy Directive has entered into force, with the aim of supporting the share of renewables in the total energy consumption of the EU, increasing the binding target for 2030 to 42.5%, with the ambition to reach 45% [4].

During 2024, the increase in global renewable installed capacity accounted for 585 GW. An annual increase rate of 15.1% lead by solar technology followed by hydroelectric energy [5]. Nevertheless, flexibility issues arise due to the intermittency of renewable energies. The scalability of them in the desired future energy mix brings with it the opportunity for other types of technology to give that stability to the grid and ensure the supply of demand.[6]. In addition, negative prices, market saturation and congestion pose major challenges to the development of renewable energy.[7].

The development of new storage systems and the diversification of portfolios will mitigate the negative sides from the renewable energy technologies. In the case of Li-ion BESS, it seems to be a very convenient solution as prices have significantly decreased over the past decades. According to the International Renewable Energy Agency (IRENA), battery storage project costs dropped by 89% between 2010 and 2023. [8] Additionally, this technology allows a wide range of applications as operational strategies, feasibility assessments, and control algorithms.[6]

This thesis assesses the suitability of a Battery Energy Storage System (BESS) in two markets using two distinct approaches. In the automatic Frequency Restoration Reserve (aFRR) market, a perfect-foresight benchmark is established against which various trading strategies are compared, and a sensitivity analysis is conducted. In the Day-Ahead (DAH) market, a linear regression analysis is performed to identify the key revenue drivers for a BESS from 2019 to date. The objectives are further detailed in Section 3.

2 Literature Review

2.1 Electricity Market Structure in Europe

The liberalization of the European Electricity Market started with the Directive 96/92 [9]. The regulation has suffered different reforms second included the Directive 2003/54 and Regulation 1228/2003 [10] trying to achieve a single and integrated European electricity [11] that would enhance supply security, lowers prices through competition, improve efficiency, support renewable energy integration, and protect vulnerable consumers.

As electricity is a non-storable good, it has to be consumed by the time it is produced. The wholesale markets are organized in different types of markets: energy markets and Ancillary Services markets [12]. This separation promotes the efficiency of the systems by adequately pricing the different activities. The current trading time frames of the internal electricity markets are divided into Forward markets, Day-Ahead Market, Intraday market, Balancing market and the Continuous day after market. A temporal scheme can be seen in Figure 1. The Transmission System Operators (TSOs) are the responsible entity to guarantee the efficient performance of the Electricity markets [13].

The forward market allows market participants to stabilize their future cash flows and hedge their positions. Therefore they can secure their businesses against the risks of market volatility. [14]. Currently, the European electricity forward market is facing some issues such as insufficient liquidity, accessibility, competition and transparency as well as concentrated market power. ACER (Agency for the Cooperation of Energy Regulators) proposes changes to improve EU electricity forward markets.[15]

In the Day-Ahead Market, the suppliers submit their bids at their marginal price one day before the actual delivery. The market is in charge of matching the bids of supply and demand and set the electricity price. In order to improve the market liquidity and originate less volatile electricity prices, in the EU the Single Day-ahead Coupling (SDAC) was confirmed. [1]. As a solution, the MCO Plan approved by all EU National Regulatory Authorities on 26 June 2017 confirms the adoption of the "Price Coupling of Regions" (PCR) project. EUPHEMIA (acronym for Pan-European Hybrid Electricity Market Integration Algorithm) has been used to allocate the electricity prices across Europe, maximizing the overall economic surplus and increasing the transparency of the computation of prices and flows. [16].

The Intraday Market electricity is traded within the delivery day. It allows the adjustments real-time, to meet actual demand and supply conditions throughout the day. XBID (Cross-Border Intraday) is a solution that enables continuous trading of electricity across multiple European countries through a common IT system, enhancing the efficiency and integration of the European Intraday market. [13]

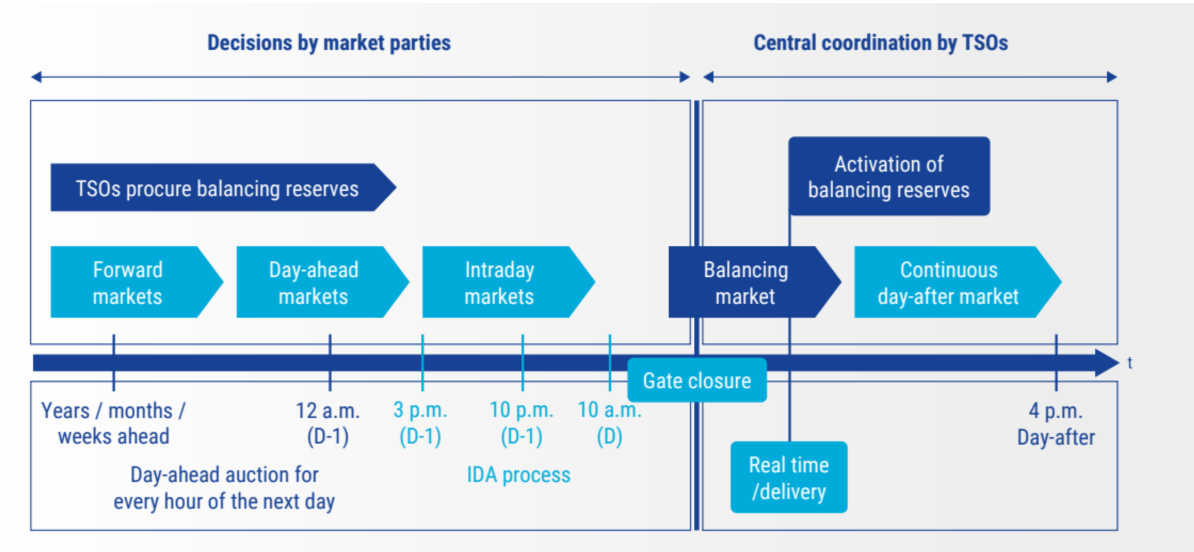


Figure 1: Market Structure [13]

The balancing markets actions and processes through which transmission system operators (TSOs) continuously ensure the maintenance of system frequency within a predefined stability range, as well as compliance with the amount of reserves needed with respect to the required quality. [17]. The different services offered by the TSO are the active power ancillary services, load–frequency control (LFC) and reactive power ancillary services (voltage control). [12]. The TSO is the entity responsible of securing the energy supply and operation of the Power Systems Services. Ancillary Services are separated from the energy production, even though it is provided by the generator. It can be mandatory or remunerated under market driven mechanisms.

European TSOs use different processes and products to balance the system and restore the frequency within acceptable ranges.[17]

- **FCR Frequency containment reserve** . The power reserves to maintain system frequency after the occurrence of an imbalance. It is in charge of stabilise the frequency after the disturbance at a steady-state value within the permissible maximum frequency deviation by a joint action of FCR within the whole synchronous area.
- **Frequency restoration reserves with automatic activation (aFRR) and manual activation (mFRR)**.The active power reserves that restores the frequency towards a set point and replaces the activated FCR. The frequency restoration process is triggered by the disturbed LFC (load-frequency control) area.
- **Replacement reserves (RR)** The active power reserves available to restore or support the required level of FRR in case of possible additional system imbalances. This replacement reserve is activated in the disturbed LFC area.

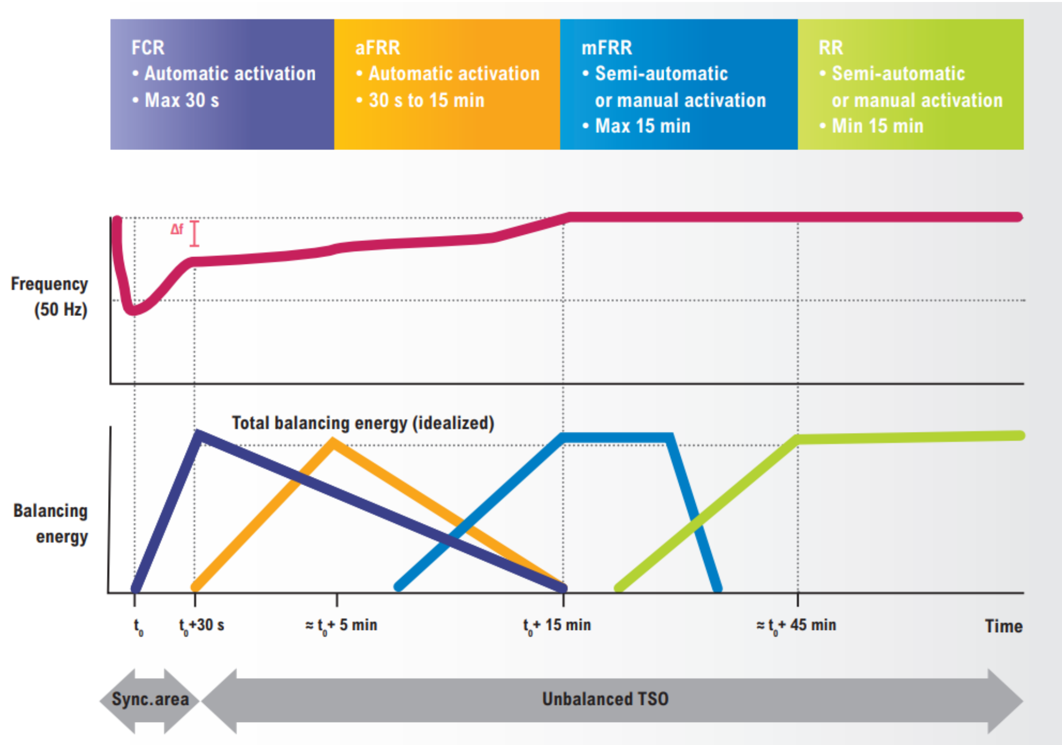


Figure 2: Balancing mechanism [17]

2.2 Focus on the Spanish Market

The Spanish market operates through a sequence of markets. Each day is divided into 24 hourly periods. The daily energy market is the first market to be settled where most of the energy is cleared. When the daily market is cleared the System Operator performs the congestion management analysis that might modify the generation dispatch.In the congestion management market, the generators solve technical constraints and are dispatched according to the bids submitted to the congestion management market. [12]

When the network constraints are solved, the secondary reserve market is executed. Consequently, there are six intra-daily markets. It can be stated that in Spain, only the first intra-daily market is significant in terms of energy dealed. The rest of the markets are normally used to fix operative mismatches or infeasibles schedules. [12].

Primary control is the automatic delivery of power to a generating unit due to frequency deviations. Because measuring and assessing quality is highly challenging, the primary control has been established as a mandatory, non-remunerable AS. When there is a system disturbance, the primary control can prevent significant frequency fluctuations.However, it does not restore the system frequency to its scheduled value, resulting in a frequency deviation in the system's steady state. The purpose of secondary control (AGC, automatic generation control) is to return the system frequency to its scheduled value.Primary regulation requirements stipulate that generator groups must allow a droop in their regulators to vary their load by 1.5% of nominal power. [18]

The secondary control operation in Spain relies on the results of an hourly secondary reserve market, where the generating units submit bids for up- and down-reserves (in MW) along with their associated prices (€/MW). The bids are sorted by price and the cheapest are accepted until the total reserve margin required by the system operator is met, which is determined by various criteria, including UCTE (Union for the Coordination of Transmission of Electricity) recommendations. UCTE recommends an up reserve value close to $6\sqrt{Pmax}$ (where Pmax is the maximum forecast hourly demand) for transition hours, while the down reserve can range from 50% to 100% of the required up reserve based on the system conditions. [12]

Tertiary control, also known as manual frequency restoration reserve (mFRR), is an active power ancillary service activated to restore the secondary reserve used during automatic generation control (AGC) operations. In the Spanish electricity system, a specific tertiary reserve market has been established, which is only called and cleared if the secondary reserve margins are exhausted [12].

Generators are responsible for providing tertiary control services. The bids submitted to the tertiary market must consist of the active power variations (increases or decreases) that generating units are capable of executing within 15 minutes and maintaining for at least 2 hours [18]. Each day, after the secondary reserve market is cleared, the system operator defines a minimum required amount of tertiary reserve. This value is calculated hourly and is equal to the rated power of the largest unit in the system plus 2% of the forecasted demand for each hour [18].

All generating units must offer their total available tertiary reserve, complying with the aforementioned criteria. If the total reserve offered does not meet the system requirements, the system operator will connect additional generating units to ensure compliance. Only the tertiary energy actually delivered by the activated units is remunerated, based on the energy price submitted in the bid [12]. Recent studies have also evaluated the technical viability and increasing role of renewable sources, particularly wind farms, in participating in the tertiary reserve market under favorable grid conditions [19].

The balancing service, also referred to as the deviation management market, is executed when significant differences between forecasted and real-time generation or demand are expected, typically due to large unit outages or demand forecast errors. The balancing market is activated by the system operator for those hours not covered by the intraday markets, specifically when the expected imbalance exceeds 300 MWh [12].

Participation in this market is limited to generating units and pumped-storage facilities. These resources are rescheduled to correct the imbalance, and only the dispatched energy is remunerated. Due to its corrective nature and limited scope, this market does not rely on strategic bidding like the day-ahead or tertiary markets. Instead, it serves as a final layer of operational adjustment to preserve system reliability. As highlighted by [20], the current market design presents challenges for the full participation of intermittent renewable generators in balancing services, although regulatory and technical improvements are progressively being introduced to enhance their contribution.

2.3 Battery Energy Storage Systems (BESS) Market Overview and Practical Applications

2.3.1 Battery Technologies and Characteristics

The physical nature of electricity requires that supply and demand remain balanced at all times. Currently, this balance is generally maintained by flexible fossil fuel-powered generators. [21]. Nevertheless, to reduce carbon emissions, these must be replaced by low-carbon alternatives. Each country opts for different candidates for substitution such as wind, solar photovoltaic and nuclear energy, depending on resource availability, cost and societal preferences. These sources, however, are either variable (wind and solar PV depend on weather) or inflexible (nuclear is typically operated at a constant output for economic and safety reasons). As shown in 3 from [22], when flexible assets are removed, demand is not fully met at all times, showing how flexibility is essential. The four main options to provide flexibility in the electricity system are: flexible power generation, electricity network interconnection, demand-side response, and electricity storage.

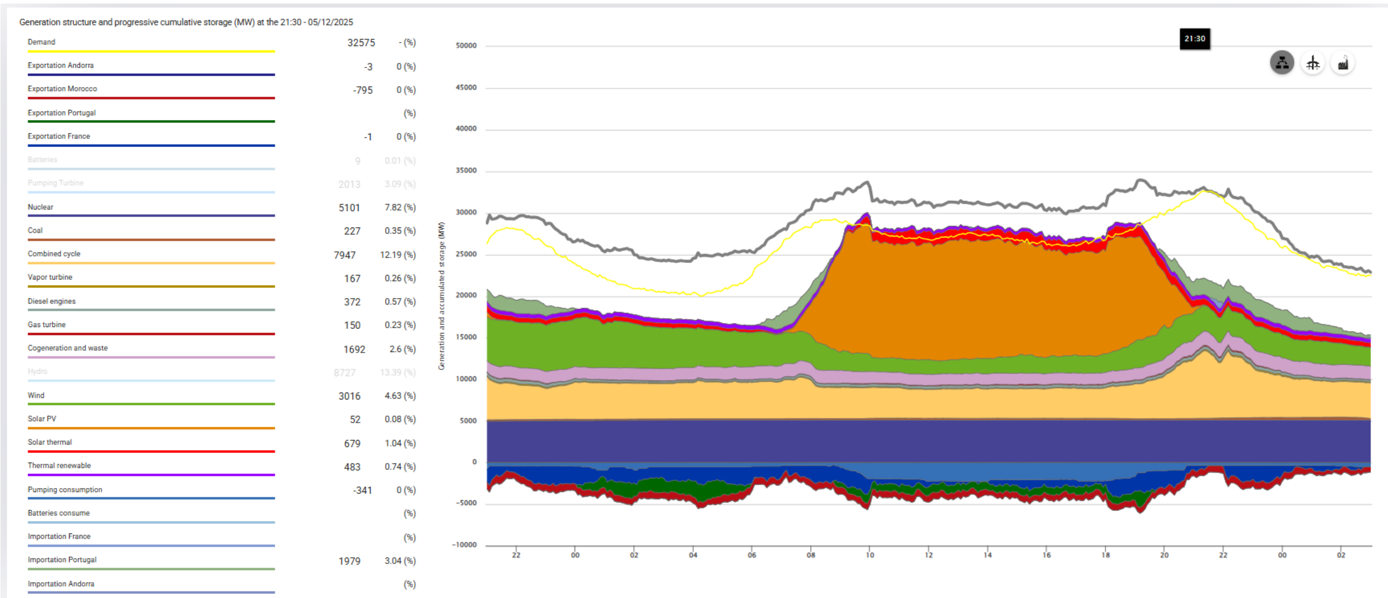


Figure 3: Spanish Supply and Demands Curve Subtracting the flexible Installed Capacity 13 May 2025

Energy storage is commonly classified into five categories: chemical, thermal, mechanical,electrical, and electrochemical. The first four categories refer to the form in which energy is stored. The final category classifies battery technologies based on the electrochemical reactions that take place within them. Energy is stored as the electrochemical potential between two materials that could react to form a new one. The net chemical energy of forming the new material (Gibbs free energy) is balanced by the electrostatic energy between the two separated materials.

The dominant concepts are sealed and flow batteries. In sealed batteries, electrodes constitute the active material separated by an ion-conducting electrolyte. All components are in a confined battery cell. In flow batteries, the active material is not the electrode itself but two liquid electrolytes that can be circulated and stored outside of the system.4 Figure 3.6 shows both concepts with the examples of lithium-iodine (sealed) and vanadium flow batteries. [23] Variations are based on electrode chemistry/structure and design Cathode chemistry: lithium cobalt oxide (LCO), lithium manganese oxide (LMO), nickel manganese cobalt (NMC), nickel cobalt aluminium (NCA), lithium iron phosphate (LFP)

2.3.2 Batteries in the Grid Converters

The shift towards renewable energy sources such as wind and solar has led to a significant reduction in conventional synchronous generators within power systems. These traditional generators inherently provide rotational inertia, which helps dampen frequency deviations during disturbances. With their displacement, maintaining system stability becomes increasingly challenging, especially in terms of inertia and frequency response.

Battery Energy Storage Systems (BESS) are emerging as key assets in addressing these challenges. Although BESS do not provide physical inertia by default, they can emulate inertia through advanced control strategies such as Virtual Synchronous Machine (VSM), droop control, or synthetic inertia methods. These approaches enable inverters to mimic the inertial response of rotating machines by rapidly adjusting power output in response to frequency deviations [24]. Some of the grid converters that use batteries are written in A.1

Several studies have demonstrated that BESS can provide frequency containment and regulation services faster and more accurately than traditional generators [25]. Furthermore, they can support voltage stability by injecting or absorbing reactive power through grid-connected converters [26]. However, wide-scale integration of these devices requires advanced coordination among multiple systems, high-speed communication infrastructure, and harmonized regulatory frameworks [27].

A growing area of discussion is the compensation for inertia-like services. Germany, for instance, is opening its power system to BESS participation in inertia services and is considering grid fee reforms to reflect the added system value these technologies provide [28]. This trend points to the importance of developing new market products that reward fast-response assets for their role in grid stabilization.

From a technical standpoint, grid converters interfacing batteries with the power system operate at very short time scales, enabling services such as Fast Frequency Response (FFR), fault ride-through, and voltage support. Predictive control algorithms and robust energy management systems are essential to maximize the operational flexibility and stability support provided by BESS. Moreover, their effectiveness can be significantly enhanced through coordinated control strategies across transmission and distribution levels [25].

2.3.3 Market Participation and Revenue Streams

As has already been mentioned, storage systems are essential for future systems with intermittent renewable energy sources [6]. By the end of 2023, BESS capacity in Europe reached 35.9 GWh, with a projection for 260 GWh of battery storage by 2028.[29].

From all the uses that BESS may offer in the electric system, the markets in which the battery might be participating will direct the strategy used like arbitrage and ancillary services, such as frequency response and voltage support [30]. Arbitrage is exploiting temporal price differentials, buying electricity when prices are low (usually during off-peak hours) and selling it when prices are high (typically during peak demand periods). The most typical strategies of arbitrage are: Long-term arbitrage, mirror arbitrage, back-to-back arbitrage and static and moving average arbitrage. [31]

Each market in which Battery Energy Storage Systems (BESS) can participate has its own characteristics, benefits, and revenue opportunities. In the Day-Ahead (DAH) market, the most common strategy is arbitrage, which involves purchasing electricity when prices are low and selling it when prices are high. This market offers high liquidity, facilitating the buying and selling of energy. In the intraday market, there is a greater opportunity to capture price spreads, and positions can be realigned more easily in real-time markets. [32] The Frequency Containment Reserve (FCR) market offers higher revenues per band and activation. The decoupling of upward and downward bids has improved efficiency in this market. Utilizing batteries in the Manual Frequency Restoration Reserve (mFRR) and Replacement Reserve (RR) markets allows for optimization of battery use in more flexible markets. [33] [34]

Because BESS can choose whether or not to provide a service at a specific cost, it will only be used if the market price for the service is sufficient to cover both the marginal costs and operational cost of the battery. [6] The operational strategies of BESS will be designed to assess the potential of European markets, taking into account the specific characteristics of each one. This project will aim to adapt these strategies to the unique features of each market.

2.3.4 Key Revenue Drivers for Battery Energy Storage Systems

Revenue depends on market design, operational constraints, and technical specifications of the asset. It will primarily depend on the different markets (Day-Ahead, Intraday, ancillary), as each offers distinct revenue streams. Understanding these drivers is key to assessing BESS economic potential in varied markets. [35]

- **Energy Prices & Volatility**
  Prices are key to capturing maximum possible revenue, and each market has its own particularities. Intra-day and inter-hour spreads enable "buy low, sell high." Day-Ahead and Intraday markets have different volatility profiles from which we can benefit. Similarly, each region under analysis presents different patterns, with frequent price spikes leveraging higher arbitrage revenue. [35], [36]

- **Battery Duration & Efficiency**
  Battery characteristics both enable and limit how price spreads can be captured. The energy-to-power ratio sets how many hours of discharge are available. Longer-duration batteries capture more value, offering greater operational flexibility. Additionally, higher round-trip efficiency increases net profit per cycle, as there are fewer conversion losses and therefore more energy can be sold in the market. [36], [37]

- **Cycle Life & Degradation Cost**
  High-frequency cycling accelerates capacity fade. In the case of Spain, degradation costs (€/MWh) must stay below thresholds (15–50 €/MWh) for long-term viability. Operational strategies must therefore balance revenue maximization with battery preservation. [37], [38]

- **Ancillary Services Participation**
  BESS can participate in frequency regulation markets (FCR, aFRR) and capacity reserves. Payments in these markets tend to be more stable and sometimes higher per MW than in pure arbitrage. Service "stacking" (combining multiple products) maximizes total revenue. [39], [40]

- **Gas & CO_2 Prices**
  In marginal cost-based markets, electricity is priced off fuel costs, since the marginal technology on the merit order curve sets the market price. This typically occurs when renewable prices are low and demand is high. Fuel prices also depend heavily on international events (e.g., wars or chokepoint closures such as the Strait of Hormuz). The emission factor (kg CO_2/kWh) adds a CO_2 price component:

$$\text{Running Cost} = \frac{\text{Fuel Price}}{\text{Efficiency}} + \text{Emission Factor} \times \text{CO}_2\,\text{Price}$$

  Fuel and CO_2 price swings drive spreads and volatility, impacting revenue. [41], [42]

- **Market Saturation & Competitive Dynamics**
  The growing capacity of all flexibility-providing technologies leads to a "crowding" effect: increasing BESS capacity erodes price spreads. To remain competitive in arbitrage, increased competition requires multi-service stacking. [35], [39]

- **Regulatory Framework & Policy**
  Regulations set by national and international bodies can limit or enhance revenue growth for flexibility technologies—for example, Spain's gas price cap in 2022. Price zones, auction mechanisms, and subsidy schemes shape revenue opportunities. Market entry requirements (size thresholds, collateral, testing) can act as barriers. Policy shifts (e.g., the emergence of carbon markets) also redefine which services are most valuable. [41], [43]

Understanding these factors enables more accurate forecasting of BESS revenues and supports the design of adaptive operational strategies that respond to changing market conditions.

2.3.5 Future Trends and Perspectives in Battery Energy Storage Systems

Battery Energy Storage Systems (BESS) are poised to play a pivotal role in the transition towards a decarbonized power system, driven by the increasing penetration of variable renewable energy sources (RES) and the need for enhanced flexibility and ancillary services.

Recent forecasts indicate that European storage capacity will rise from around 60 GW in 2022 to over 200 GW by 2030, potentially reaching 600 GW by 2050, with stationary batteries contributing more than 100 GW [44]. This rapid growth is catalyzed by the critical role of BESS in grid stabilization services such as Frequency Containment Reserve (FCR) and automatic Frequency

Restoration Reserve (aFRR).

The integration of BESS into energy and ancillary service markets has been evolving, with new regulatory guidelines promoting active state-of-charge management and market-based recharging strategies, notably in Europe [44]. National assessments, like the Spanish National Resource Adequacy Assessment (NRAA), underscore storage's importance in mitigating adequacy risks during high RES scenarios [45]. New market designs also facilitate multi-market participation, allowing batteries to simultaneously engage in day-ahead markets, frequency regulation, and capacity markets. Studies have demonstrated that stacking revenue streams can significantly enhance BESS profitability compared to single-market strategies [46].

Technological advancements are further driving BESS deployment. Progress in battery chemistries, particularly lithium-iron-phosphate (LFP) and emerging technologies like solid-state and sodium-ion batteries, is improving cost structures, safety standards, and cycle life. Moreover, hybrid storage configurations that combine batteries with ultracapacitors are being investigated to optimize the delivery of fast response services [47].

A noteworthy trend is the integration of BESS with large-scale photovoltaic (PV) plants. Techno-economic analyses have revealed that coupling BESS with PV installations enhances revenue streams by enabling participation across diverse market layers, including day-ahead trading and ancillary services [46].

Beyond technological progress, strategic market participation is crucial to ensuring profitability. Emerging frameworks recommend adopting bi-level optimization models that treat BESS as price-makers instead of price-takers, considering real-world non-convex market constraints [48]. Additionally, heuristic methods such as Particle Swarm Optimization (PSO) are being leveraged to address the complexity of bidding strategies in contemporary electricity markets.

Incorporating battery degradation models into operational strategies has also become imperative. Accurate modeling of cycle and calendar aging processes is key to maintaining profitability throughout the battery's lifetime, especially when targeting frequency regulation markets, where high cycling rates can accelerate degradation [46]

While electrochemical batteries dominate the current storage landscape, alternative technologies are attracting increasing attention. Carnot batteries, which convert electricity into thermal energy and reconvert it back into electricity, present a promising solution for long-duration storage. Recent studies suggest that Carnot batteries, due to their scalability and cost advantages at longer storage durations, could complement conventional BESS deployments, particularly in systems with high shares of wind and solar power [47].

In summary, the future landscape of BESS is being shaped by a combination of expanding multi-service market participation, technological innovation, strategic optimization approaches, integration with renewables, and the emergence of alternative long-duration storage technologies. These developments position BESS—and complementary systems like Carnot batteries—as critical enablers of resilient, flexible, and low-carbon power systems.

3 Research Motivation and Objectives

3.1 Motivation

The increasing penetration of variable renewable energy sources (RES) into power systems poses significant challenges for maintaining the balance between supply and demand. This situation intensifies the need for flexible resources capable of delivering grid services and supporting system stability. Among these resources, Battery Energy Storage Systems (BESS) stand out thanks to their fast response time and ability to participate in multiple markets.

In the aFRR market, a deterministic model is used to compute the maximum theoretical revenue under perfect foresight. This benchmark is subsequently employed to evaluate the effectiveness of several operational strategies, including dynamic bidding approaches that adapt to historical market conditions.

For the Day-Ahead market, the goal is to identify and analyse the key revenue drivers influencing BESS profitability—such as price volatility, renewable penetration and the evolution of gas prices over time.

3.2 Research Questions and Objectives

The primary objective of this thesis is twofold. In the aFRR market, the study compares a range of trading strategies—energy-only versus combined energy–capacity participation against the deterministic benchmark obtained via back-testing. Different bid-pricing and volume-sizing rules are tested with the aim of maximising economic profit while keeping operational characteristics, such as the average number of cycles per day, within acceptable limits. The analysis also investigates how battery size (1 h, 2 h and 4 h durations) affects revenue capture. In the Day-Ahead market, the objective is to determine, through regression analysis, the variables that have influenced BESS revenues in Spain during recent years.
The analysis is structured along two axes:

- **aFRR Market:**
  - Estimate the maximum theoretical revenue that a BESS could achieve under perfect market foresight.
  - Develop and test several realistic trading strategies, including energy-only, combined energy–capacity participation and dynamic bidding strategies.
  - Evaluate each strategy's ability to recover a meaningful share of the benchmark revenue, taking into account operational constraints (e.g. number of cycles, energy limits).
  - Assess the sensitivity of the results to key parameters such as premium adjustments and battery duration.
- **Day-Ahead Market:**
  - Conduct a revenue-driver analysis to identify which market and technical factors most strongly influence BESS revenue (e.g. gas running cost, renewable generation, number of cycles).

– Apply statistical tools (correlation analysis, regression) to explore relationships between these variables and observed revenues.
– Provide a qualitative and quantitative assessment of the conditions under which arbitrage in the Day-Ahead market becomes attractive.

Based on these two complementary approaches, the thesis aims to provide a comprehensive understanding of the economic potential of BESS and their strategic behaviour in the Spanish electricity market.

3.3 Outline of the Methodological Approach

This thesis applies a dual methodological approach to assess the market potential of BESS in Spain. For the aFRR market, a backtesting framework is used to benchmark revenues under perfect foresight and evaluate the performance of several trading strategies. For the Day-Ahead market, a statistical analysis identifies key variables influencing profitability, based on historical market data. This structure enables both a quantitative and qualitative assessment of BESS performance under real market conditions.

4 Methodology

This chapter outlines the methodological framework adopted to evaluate the economic performance of Battery Energy Storage Systems (BESS) in the Spanish aFRR electricity markets and. While in DAH drivers systematic analysis will head us to identify and quantify what factors drive or limit the revenues obtained by a battery participating in this market. It provides an overview of the modeling approach, key assumptions, and the trading strategies implemented, followed by the data sources used and model limitations.

4.1 Scope and Approach

This thesis evaluates the market potential of Battery Energy Storage Systems (BESS) in two key segments of the Spanish electricity market: the automatic Frequency Restoration Reserve (aFRR) and the Day-Ahead (DAH) market.

For the **aFRR market**, a backtesting framework is developed to simulate multiple BESS trading strategies using historical data, ranging from idealized deterministic models to more realistic adaptive heuristics.

For the **DAH market**, a statistical linear regression analysis is conducted based on battery revenue drivers. A linear regression model is applied, using 80% of the available data for training and the remaining 20% for model validation.

4.2 Modeling Assumptions

4.2.1 Automatic Frequency Restoration Reserve (aFRR) Assumptions

To ensure realistic and consistent modeling, the following assumptions were made for the aFRR market simulation:

- **Marginal battery size**: A 1 MW BESS is assumed. The battery is considered a price-taker, meaning it does not influence market-clearing prices. Thus, the merit order remains unaffected regardless of whether its bids are accepted.
- **Operation and Maintenance Costs**: These are considered negligible and are excluded from the model. No minimum activation threshold is imposed.
- **Bid acceptance and Direct activations**: If the bid price is below the market-clearing price, full activation is assumed for the 15-minute product. Activation time is not modeled due to lack of publicly available data.
- **Market access and Procurement**: The battery is assumed to have access to both energy and capacity markets. To maintain energy balance, any required energy is assumed to be procured from the intraday market. The intraday price is assumed to match the imbalance price, as these converge when approaching delivery time.
- **Bidding deadlines**: Energy bids can be submitted up to 25 minutes before delivery, and capacity bids before 20:00 on the day before delivery, in accordance with REE regulations [49].
- **Product symmetry**: The model assumes the symmetric structure of aFRR products as offered in the Spanish market.
- **Curtailments**: Grid congestion and locational constraints are not modeled, as no grid topology is implemented. Curtailments are excluded to maintain model simplicity.
- **Seasonality and Volatility**: Market price volatility is assumed to be constant throughout the year. As only three months of data are simulated, revenues are annualized by multiplying by four.

4.2.2 Day-Ahead Market Analysis Assumptions

The analysis of the Day-Ahead Market was based on a linear regression approach, aiming to estimate the impact of market and technical variables on the daily simulated revenue of a battery system. The key assumptions and steps in the modeling process are listed below:

- The input dataset covers daily values from 2019 to 2025 and includes prices, renewable generation, fuel costs, and estimated battery operation metrics.
- A multivariable linear regression model was used to evaluate revenue drivers.
- Data was grouped by season and month to account for temporal variability in market conditions.
- Columns with more than 50 percent missing values were dropped; only numerical variables were considered.
- The dataset was split into 80 percent training and 20 percent testing subsets.
- Evaluation metrics included R^2 and Mean Squared Error (MSE).

- Additional visual analysis was carried out using scatter plots to reveal patterns, correlations, and validate assumptions of linearity.

These assumptions enabled a transparent and interpretable framework to assess under which market conditions arbitrage in the DAH market becomes attractive for BESS, and which external variables most strongly influence the profitability.

4.3 Model Description and Strategy Design

This section describes the core modeling framework and trading strategies developed to simulate the participation of BESS in the aFRR market. All strategies use historical market prices, battery constraints (power, energy, efficiency), and a 15-minute time resolution.

Both deterministic cases will serve as a benchmark to analyze what revenue share our trading strategies will capture, introducing uncertainty as well as restrictions on cycles per day to ensure correct use of my battery as explained in [23] extending battery life.

4.3.1 Deterministic Strategy: Energy-Only Optimization

A dynamic programming approach is implemented, assuming perfect foresight of market prices. In order to explore the all the operational possibilities, the energy levels are discretised and backward induction is used to compute the optimal value function. Figure 18 illustrates this process, showing how all possible battery configurations at different power levels are considered. The optimal power output that maximies final revenue will be chosen. Once the optimal dispatch path is obtained, a forward simulation is applied starting from a 50% state of charge. All the technical features of the battery such as the round-trip efficiency, cycle constraints are respected, battery energy and power constraints are respected. Only energy revenue is considered; capacity revenue is excluded.

4.3.2 Deterministic Strategy: Energy + Capacity Optimization

This extends the previous strategy by including revenue from upward reserve capacity. The battery optimizes both energy dispatch and capacity reservation at each time step considering the market constraints shaped by [49] . A minimum energy level is required to participate in the capacity auction. To reach this threshold levels the intraday market is modeled to supply the needed energy, The optimal strategy is obtained using backward dynamic programming and validated using forward simulation.
Figure 4 shows the method used to ensure the battery's energy reserves match the requirements for participation in both energy and capacity auctions. The 'Committed Energy Threshold' represents the lowest energy level a battery must maintain to participate in the capacity market. The energy auction defines the 'Pre-Allocated Energy' level. To ensure the 'Final Energy Set' meets the thresholds set by the capacity auction, additional energy must be acquired from the intraday market, identified in the graph as 'Intraday Energy Adjustment'.

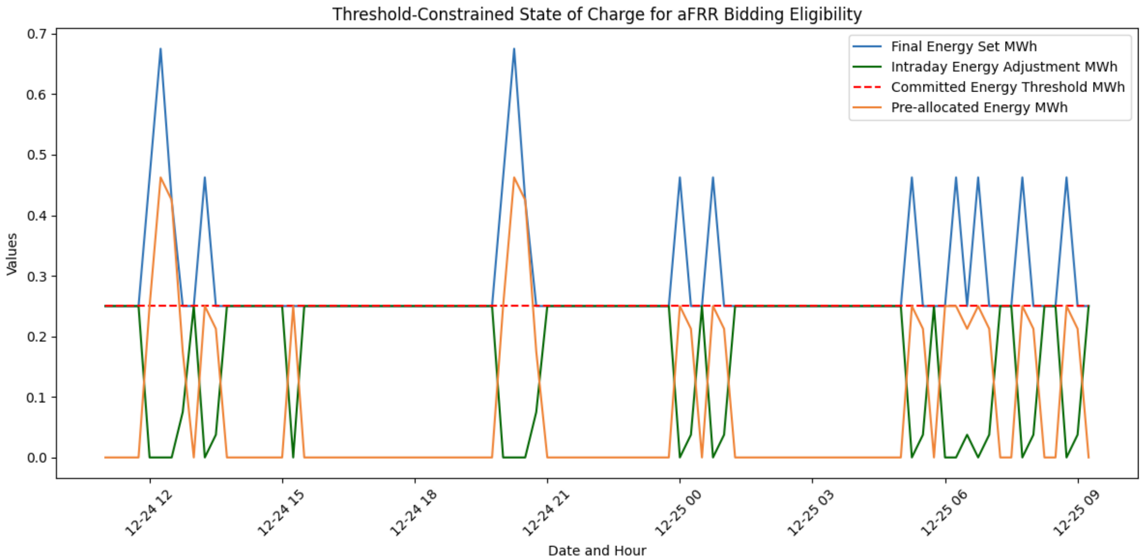


Figure 4: Threshold-Constrained State of Charge for aFRR Bidding Eligibility

4.3.3 Heuristic Dynamic Bidding – Energy-Only Strategy

In this case, the first trading strategy is analyzed. The objective is to capture the largest difference between bid and ask prices, which are unknown beforehand. As stated in the REE regulations [49], changes can be made to the aFRR bids up to 25 minutes before delivery. Thus, two different strategies are considered for bid modeling: the Pricing Bid Strategy and the Volume Bid Strategy.

Figure 5 illustrates that the price strategy enables setting a bid price based on the lowest of the previous 8 known values. For both selling and charging bid prices, additional parameters (Premiums) are added, allowing the modification of the bid price to ensure battery participation during higher-priced periods and thus maximizing profit.

In the Volume Bid Strategy, revenue maximization is targeted primarily through maximizing energy utilization, constrained by the battery's power and remaining energy. The charge bid is limited by the battery's available energy and charging capacity. In both scenarios, the battery's charge and discharge efficiencies are considered.

A sensitivity analysis is conducted to determine the optimal combination of parameters for revenue maximization and effective battery operation. Different premiums are varied. If the bid price falls below the market-clearing price, it is considered an activation trigger. Activations last 15 minutes, during which operational battery vectors, such as power, energy, and cycles per day, are continuously updated.

Figure 5: Pricing strategy for upward and downward bids with Up Premium =0 and Dn Premium = 0

4.3.4 Heuristic Strategy: Static Capacity Sensitivity with Price Premiums

This case involves a sensitivity analysis of capacity, Up Premium, and Dn Premium. Each simulation uses a fixed combination of these three variables. The objective is to identify the maximum revenue achievable while managing the number of cycles per day. Capacity ranges from 0 to 1 MW, the battery's maximum power, as specified in 4.2.1. To determine the minimum threshold required for participation in the capacity auction, the strategy outlined in Figure 4 is applied. Metrics such as revenue, energy throughput, and average cycles per day are gathered for each combination.

4.3.5 Adaptive Strategy: Optimized Capacity and Price Premium Based on 3 Previous Days

This scenario models the typical operation of a battery trading algorithm by determining the optimal combination of parameters based on prices observed over the previous three days. A loop is executed through potential capacities and premiums, with the optimal combination selected for the following day. Adjustments to premiums and capacity vectors are made prior to 20:00 of the preceding day, adhering to regulations outlined in [49]. Additionally, the model engages with the intraday market for energy adjustments to comply with the thresholds depicted in Figure 4.

4.3.6 Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day

This case models the typical daily operation of a battery trading algorithm by determining the optimal hourly combination of capacity and premiums based on prices observed on the previous day. Optimal hourly combinations are identified and premiums and capacity vectors are adjusted before 20:00 of the preceding day, in line with regulations described in [49]. Figure **??** is an example of the optimal hourly premiums. As in previous scenarios, the model contracts with the intraday market to meet the necessary energy thresholds according to Figure 4.

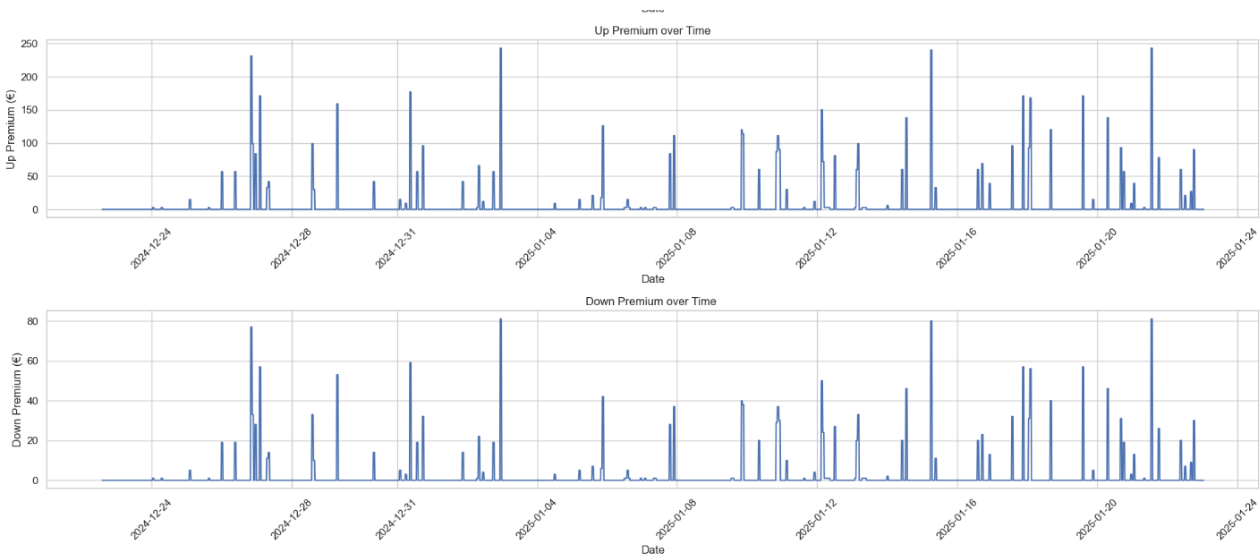


Figure 6: Example of the adjusted Premiums per hour (€/MWh)

4.4 Regression Model for the Day-Ahead Market

The objective of this model is to quantify the influence of various market and technical variables on the simulated daily revenue of a battery operating in the Spanish Day-Ahead (DAH) electricity market over the period 2019–2025. 4.4 summarizes the predictors included in the analysis:

- **Daily average, maximum and minimum DAH prices** (€/MWh)
- **Gas price** (€/$\mathrm{MWh_{th}}$)
- **CO_2 price** (€/t)
- **Renewable generation (solar and wind)** (%), including the production from each technology
- **Load** (MW), including the calculation of residual load
- **Installed capacity per technology**

To compute the battery revenue, a proprietary Python-based simulation tool developed by Centrica Energy was used. This model estimates the potential revenue based on the daily price spread between the maximum and minimum values, while respecting the physical constraints of the battery, such as rated power, energy capacity, and a predefined limit on the number of daily cycles.

The dataset was split into 80 % for training and 20 % for testing. The model's performance was evaluated using two metrics: the coefficient of determination (R^2) and the Mean Squared Error (MSE). To capture seasonal and temporal variability in market conditions, independent regression models were trained for each season and for each calendar month.

4.5 Data Sources

- **aFRR market prices**: Historical activation prices obtained from Red Eléctrica de España (REE), via the Platform for Balancing Services [50].
- **Imbalance/intraday prices**: Used to simulate energy procurement during shortfalls [50].
- **Battery technical specifications**: Based on industry data and academic references [51].
- **Electricity generation data**: Historical data from 2019 to 2023 retrieved from the REE open-data portal (ESIOS) [52].
- **Installed capacity**: Annual values obtained from REE's Adequacy Report [53].
- **Gas prices**: Iberian wholesale prices used as a proxy for the marginal cost of gas-based generation [54].

4.6 Limitations

- **Limited data**: Only four months of historical market prices were available for the aFRR simulation.
- **Market opacity**: Lack of visibility into bidding strategies and competitor behavior due to limited public disclosure in Spain.
- **No degradation modeling**: Battery aging and performance degradation are not explicitly modeled.
- **Simplified geography**: Locational constraints and grid congestion are not considered.
- **Computational cost**: Simulations involving grid search and adaptive strategies are computationally intensive, limiting the time horizon analyzed.

5 Model Implementation

This chapter will detail the computational implementation of both the aFRR trading strategies and the DAH driver analysis. All models have been written in Python. The market data is historical and has been obtained from the sources detailed in 4.5.

5.1 Battery Modeling

The physical characteristics with which we have modeled the battery have been

- Power capacity (1 MW for all cases),
- Energy capacity (1 MWh, 2 MWh, and 4 MWh),
- Charging/discharging efficiency (round-trip efficiency of 85%),
- State of Charge (SOC) limits,
- Maximum allowed cycles per day.

The operational features of the battery such us power and energy stored in the battery are modeled using different vectors that simulate over time. These vectors are updated according to battery bid activations, taking into account efficiencies and performances, and also are limited by operational limits on the battery.

5.2 aFRR Simulation Workflow

All simulations follow a general structure to compute battery operation:

1. Load and preprocess historical price data.
2. Initialize battery state (50% SOC) and operational vectors such as p_up, p_dn, and others.All vectors correspond to time series with a 15-minute timestep.
3. In cases involving optimization, execution of the loop to determine and characterize each strategy and decesive parameters.
4. Run a loop for each time step:
   - Determine bid prices (based on the selected strategy).
   - Compute available bid volumes (based on SOC and power limits). If adjustments are required due to daily cycle constraints, the bid volumes may be modified accordingly to ensure they do not exceed permissible battery limits.
   - Check bid acceptance conditions (compare with market price).
   - In scenarios involving capacity auctions, verify that the battery is above the acceptable threshold. If below, calculate the required energy from the intraday market and update power output and SOC accordingly.
   - Update revenue calculations, considering energy sales, capacity payments, and intraday adjustment costs.
5. Track cumulative revenue, energy throughput, and daily cycling activity.

In sensitivity analyses, nested loops are executed to systematically explore all parameter combinations, allowing analysis of the final vectors resulting from battery operations over the simulation period.

5.3 Strategy-Specific Implementation

5.3.1 Dynamic Programming Implementation

The deterministic strategies are implemented using backward Dynamic Programming (DP) which is the block that loops through output power and determines for each time step which is the optimal operation to maximise the final revenue. The Power levels are discretized in 0.05 MW increments. For each power value, a potencial future value is computed backwards like in 17. Then for each state, all feasible actions are evaluated, and the policy that maximizes immediate and future value is stored. Subsequently,a forward simulation applies the optimal actions as described in step 4 of Section 5.2.

The extended Dynamic Programming formulation for capacity participation adds an additional control variable: the reserved upward capacity. When the battery commits to providing reserve capacity, it must ensure sufficient stored energy to meet the committed capacity. If this condition is not met, the model introduces an intraday energy purchase, translated as cost impacting the revenue calculation.
The final revenue per time step m is computed as:

$$\text{Revenue}[m] = (p_{\text{up}}\,\text{price}_{\text{up},m} - p_{\text{dn}}\,\text{price}_{\text{dn},m}) \cdot 0.25 + \text{cap}\,\text{price}_{\text{cap},m} \cdot 0.25 - \text{capacity\_cost}[m]$$

where the intraday cost is

$$\text{capacity\_cost}[m] = \begin{cases} \text{price}_{\text{intraday},m}\left(\frac{\text{cap}\,0.25}{\eta_{\text{d}}} - \left(e_{\text{cur}} - p_{\text{up}}0.25/\eta_{\text{d}}\right)\right), & \text{if reserve shortfall} \\ 0, & \text{otherwise.} \end{cases}$$

5.3.2 Heuristic Strategy: Energy-Only with Price-Based Bidding

This strategy uses a forward-only simulation. Multiple premium combinations are tested in nested loops, altering the bid prices derived from historical marginal prices (see Figure 5). For each premium setting, the simulation computes revenue and average cycles per day following the workflow from step 4 in Section 5.2.

5.3.3 Heuristic Strategy: Static Capacity + Premium Sensitivity

A nested loop iterates over predefined capacity levels and price premiums. Each parameter pair is simulated over the full historical dataset. Key performance metrics—revenue, throughput, and cycle count—are logged for comparison, employing the same operational loop referenced in Section 5.2.

5.3.4 Adaptive Strategy: Daily Optimization (3-Day History)

This strategy dynamically updates the bidding parameters on a daily basis, using historical performance over the past three days. Before 20:00 each day, in compliance with market regulations [49], a nested loop with the known data from the previous days, evaluates all possible combinations of upward reserve capacity and bid premiums. The algorithm stores the best combination to be used for trading the following day and a forward loop described in Section 5.2, starting from step 4. In situations where the daily cycle count rises sharply, the bid volume is progressively constrained to maintain the cycles within acceptable operational limits, while manteining the battery performance. Daily revenue, energy throughput, and cycle count are recorded for performance evaluation.

5.3.5 Adaptive Strategy: Hourly Optimization (1-Day History)

This variant extends the adaptive logic to an hourly resolution, offering more granularity adaptability to the market time conditions. For each hour of the previous day, prior to 20:00 as explained in [49], a loop is executed to determine the optimal capacity and hourly premiums, which are stored in a vector. These represent the trading features which will be executed the following day. Then, a forward loop described in Section 5.2, starting from step 4 will be executed for each quarter-hourly step.

5.4 aFRR Computational Considerations

All operational vectors represent a 15-minute horizon. The libraries we have used to simulate the battery modeling are:

- **pandas**: for creating and manipulating time-indexed data (e.g. `date_range`).
- **numpy**: for numerical arrays, discretization (`arange`, `round`) and computations (`zeros`, `sum`, `cumsum`).
- **dataclasses**: to define the `Battery` class with typed fields via the `@dataclass` decorator.
- **matplotlib.pyplot**: to create figures and subplots for line, stack and scatter plots.
- **seaborn**: to apply the "whitegrid" style and draw high-level line plots.
- **matplotlib.dates**: to format datetime ticks on the x-axes of the plots.

The arrays for storing the results are:

- **up_marginal_price_vector**: 15-minute series of "up" market prices used in DP and simulation loops.
- **dn_marginal_price_vector**: 15-minute series of "down" market prices used in DP and simulation loops.
- **energy_levels**: discretized SOC levels from `e_min_mwh` to `e_max_mwh` in 0.05 MWh steps for the DP state grid.
- **actions**: possible charge/discharge powers from –1.0 MW to +1.0 MW in 0.05 MW increments for DP decisions.
- **V**: (T+1 × n_levels) DP value-function table storing the maximal future value at each time and SOC.
- **policy**: (T × n_levels) DP policy table storing the optimal action (power) at each time and SOC.
- **historical_soc**: time series of battery state-of-charge (MWh) during the forward simulation.
- **historical_action**: time series of actual charge/discharge power (MW) applied by following `policy`.
- **historical_revenue**: instantaneous revenues (€) at each 15-minute step during simulation.
- **cycles_per_day**: per-step cycle contributions when discharging, used to track battery aging.
- **verify_cycles_per_day**: rolling sum of `cycles_per_day` over the last 96 intervals (24 h) to enforce cycle limits.
- **date_index**: realistic 15-minute datetime index created via `pd.date_range` for plotting.
- **revenue_acum**: cumulative sum of `historical_revenue` to plot accumulated earnings over time.

5.5 Implementation of Regression Analysis for the Day-Ahead Market

The regression analysis described in Section ?? was implemented in Python using the `scikit-learn` library. The objective was to quantify the explanatory power of market and system variables over the simulated daily revenue of a battery energy storage system (BESS) in the Day-Ahead market.

The computational workflow followed these steps:

1. **Data preprocessing**: Variables with more than 50% missing data were excluded from the dataset. The remaining numerical variables were used directly in the regression model.
2. **Feature engineering**: Daily statistics were computed, such as maximum, minimum, and average DAH prices, residual load, and daily battery cycles. Renewable production and installed capacity data were merged per technology.
3. **Model training**: A multivariable linear regression model was trained separately for each month and season, using an 80%/20% train-test split.
4. **Model evaluation**: Performance was measured using the coefficient of determination (R^2) and Mean Squared Error (MSE) on the test subset. These metrics were recorded and compared across different time aggregations.
5. **Visualization**: Several plots were generated:
    - Scatter plots of real vs. predicted revenues.
    - Horizontal bar charts showing the absolute value of the regression coefficients.
    - Correlation plots between key input variables and daily revenues.

This implementation allowed both quantitative and qualitative interpretation of the conditions under which arbitrage in the Day-Ahead market becomes attractive for storage assets.

5.6 DAH Computational Considerations

The libraries we have used for running the grouped regression are:

- **pandas**: for DataFrame manipulation and construction of `coef_df`.
- **sklearn.linear_model.LinearRegression**: to train the linear regression model.
- **sklearn.model_selection.train_test_split**: to split each group's data into training and test sets.
- **sklearn.metrics.r2_score**: to compute the coefficient of determination on the test set.
- **sklearn.metrics.mean_squared_error**: to compute the mean squared error on the test set.
- **matplotlib.pyplot**: to plot Actual vs Predicted scatter plots and coefficient bar charts.

The arrays for storing the results are:

- **X_train**: training features for the regression model.
- **X_test**: test features for evaluating the model.
- **y_train**: training target values ("Revenue") for fitting the model.
- **y_test**: test target values for prediction comparison.
- **y_pred**: predicted "Revenue" values on the test set.
- **coef_df**: DataFrame of the top 8 variables with largest coefficients, used for bar chart.

6 aFRR Market Results

6.1 Overview of Trading Strategies

This section summarizes the trading strategies evaluated in the aFRR market. The strategies range from an idealized deterministic benchmark with perfect foresight to more realistic approaches including energy-only bidding, fixed capacity strategies, and adaptive bidding schemes that respond to market signals.

6.2 Revenue Analysis

Table 3 presents the annualized revenues and average cycles per day for each strategy for a 1MW 2h Battery.

Strategy	Annual Revenue (EUR/MW-year)	Avg. Cycles/Day
Deterministic benchmark (energy only)	270,064	4.18
Deterministic benchmark (energy + capacity)	646,752	5.34
Energy-only participation (no premium)	177,812	4.70
Energy-only participation (best premium 94/37)	190,464	2.04
Constant Capacity best case p=1MW	219,084	3.00
Best Constant Capacity and Premiums in the previous 3 days	223,596	2.10
Best Previous Capacity Shape	219,596	2.95

Table 3: Summary of annual revenues and operational metrics by trading strategy in the aFRR market (2h Battery).

6.2.1 Deterministic Strategy: Energy-Only Optimization

As explained in Section 4.3.1, the aim of this trading strategy is to establish a benchmark to determine the maximum revenue achievable under perfect foresight of aFRR market prices. In this simulation, no constraint is imposed on the number of cycles per day.

As shown in Figure 20, the average number of cycles per day exceeds the acceptable range (0–2 cycles/day) defined in [51] as a threshold to avoid excessive degradation of the battery's lifespan, reaching a value of 4.18. The battery demonstrates a high operating frequency. As can be seen in the power plot, the system continuously exploits every available opportunity for full charge and discharge, as illustrated in Figure 19. However, we will use this benchmark as the maximum achievable, since our objective is to maximize revenue and determine the revenue share that our strategies can capture—while improving battery operability by bringing our cycles per day closer to the acceptable range.

In addition, the accumulated revenue curve follows a steady and nearly linear trend, which supports the assumption that the seasonality of aFRR prices can be reasonably neglected. It can be seen in Figure 21 Therefore, annual revenue can be estimated by proportionally extrapolating the results from the simulated period as mentioned in the Section 4.2.1

6.2.2 Deterministic Strategy: Energy + Capacity Optimization

This case allows us to establish the benchmark strategy for the highest theoretical revenue participating in aFRR, ensuring full participation in both the energy and capacity auctions, As detailed in Section 4.3.2, no constraint is imposed on the mean number of cycles per day in this simulation. In this scenario, the average cycles per day reach approximately 5.34 which can be seen in Figure 22

As shown in the power plot in Figure 24, the battery operates at high frequency, consistently exploiting its full power capabilities. Also in Figure 23 it can be appreciated as the benchmark suggests that the maximum will be reached when the capacity traded in the capacity market is close to 1 although it takes various values throughout the simulated period.

Finally, the stacked revenue chart illustrates that the dominant source of revenue arises from energy trading, while capacity payments contribute a smaller but steady share. This confirms that, although capacity markets offer additional value, the primary profitability in this strategy continues to be driven by energy arbitrage, shown in Figure 25

6.2.3 Heuristic Dynamic Bidding – Energy-Only Strategy

In this case, the only revenue stream considered is energy trading, as detailed in Section 4.3.3. In the absence of premium thresholds, the battery experiences very high operational frequency, with the average number of cycles per day rising significantly. This behavior is illustrated in Figure 26. To control this, we introduce the parameters up premium and down premium, which allow us to model the bid pricing strategy in our simulation. These thresholds ensure that the battery will only be activated when prices exceed a base value, reducing unnecessary cycling while maintaining profitable dispatch opportunities.

Under the base case (no premiums), the mean cycles per day reach 4.70. By adjusting the premium values, we can effectively control the activation frequency, keeping it within acceptable operational limits and increase the trading value. Figure 27 illustrates the sensitivity of both revenue and cycling to different premium combinations.

When prioritizing maximum cycling frequency, the top-performing parameter combinations are shown in Table 4. These scenarios lead to higher degradation risk but may be of interest in short-term arbitrage strategies.

Table 4: Top 10 premium combinations ranked by mean cycles per day and anual revenue.

Up Premium (€/MWh)	Down Premium (€/MWh)	Mean Cycles/Day	Annual Revenue (€/MW)
6	0	4.679	248,636.20
7	0	4.633	249,015.04
8	0	4.614	248,955.20
10	0	4.565	249,394.84
11	0	4.543	249,709.88
9	0	4.592	248,416.88
12	0	4.507	249,285.72
13	0	4.474	248,960.40
14	0	4.448	248,218.28
15	0	4.423	247,961.52

To preserve battery health and comply with typical degradation constraints, we also identify the optimal premium combinations that yield mean cycles per day which are lower than 2.05. These results, shown in Table 5, demonstrate that it is possible to reduce cycling while significantly improving revenue compared to the base case without premiums.

Table 5: Top 10 premium combinations with mean cycles/day while [mean cycles per day < 2.05], ranked by annual revenue.

Up Premium (€/MWh)	Down Premium (€/MWh)	Mean Cycles/Day	Annual Revenue (€/MW)
94	37	2.045	190,467.49
95	36	2.050	190,012.15
92	38	2.025	189,938.81
95	37	2.027	189,672.35
94	38	2.010	189,598.43
93	38	2.014	189,545.43
91	38	2.029	189,481.07
89	38	2.046	189,474.19
90	38	2.042	189,462.53
95	38	1.994	189,045.06

With this strategy, it has been managed to capture 70 % of the revenue while reducing cycles per day by applying a fixed premium throughout the operation. These results confirm the effectiveness of premium thresholds in tuning the operation of the battery—achieving a better balance between economic performance and technical sustainability than the original energy-only strategy without activation filters.

6.2.4 Static Capacity Sensitivity with Price Premiums

In this case, the analysis examines precisely how enforcing a specific capacity in the capacity market and varying the premiums impacts revenue, as described in 4.3.4.

It is observed that 34% of the benchmark revenue is captured while reducing cycles per day by 43%. These findings can be compared with the adaptive strategies in 6.2.5 and 6.2.6, which suggest that—most of the time—it is advantageous to bid on the capacity market with the battery's full capacity.

Table 16 lists the top 10 combinations of premiums and capacity that yield the highest revenue, all of which correspond to a 1MW capacity in the capacity market.

6.2.5 Adaptive Strategy: Optimized Capacity and Price Premium Based on Previous 3 Days

This strategy is not intended to follow hourly trading patterns; rather, seasonal patterns are prioritized, and the optimum is determined from the previous three days without emphasis on time-of-day variations. Figure 30 shows the power and energy profiles of a 2 h battery operating under the "Optimized Capacity and Price Premium Based on Previous 3 Days" strategy. Figure 31 displays the capacity traded in the capacity auction for the same adaptive strategy. The optimization consistently alternates between 0 MW and 1 MW. Specifically, traded capacity is 0 MW on 10% of days and 1 MW on the remaining 90%.

Revenue captured relative to the benchmark reaches up to 34% of its value. Capacity revenue capture exceeds the benchmark, owing to a higher frequency of 1 MW trades in the capacity auction. Figure 32 shows how premiums remain at low levels most of the time.

6.2.6 Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day

This configuration enables the capacity and premiums to be optimized on a daily basis, allowing a different value to be assigned to each hour. Because the optimized premiums are submitted at the same time on the previous day, any underlying hourly pattern can be identified. Figure **??** provides an example of how the premiums are allocated across the hours. As observed in the benchmark shown in Figure 23, the optimal capacity offered in the capacity auction is 1 MW for the majority of time steps; in the present analysis, a 1 MW offer is selected in 92 % of the hours.

When this variable-capacity strategy is compared with the deterministic benchmark, it reaches 34 % of the benchmark revenue while reducing cycles per day by 45 %.

Figure 34 illustrates how the containment rules applied to the bid volumes help keep the daily cycles close to an acceptable operational value. Figure 35 shows the capacity committed in the capacity auction, and Figure 36 presents the resulting revenue and cycles per day.

6.3 Sensitivity Analyses

This section examines how battery size influences the performance of the strategies and the revenue they generate. The battery's power rating is kept at 1 MW, but its duration is varied to 1 h and 4 h. The corresponding results are presented below.

6.3.1 Deterministic Strategy: Energy-Only Optimization

Table 11 shows how different durations affect annual revenue and cycles. As battery size increases, revenues rise correspondingly, because a larger energy capacity provides greater flexibility for charging and discharging. Conversely, when the battery size decreases, the number of cycles per day tends to increase.

Table 6: Impact of battery duration on Deterministic Strategy: Energy only

Battery Size	Annual Revenue (EUR/MW-year)	Avg. Cycles/Day
1 MW / 4h	302,988	2,17
1 MW / 2h	270,064	4.18
1 MW / 1h	238,112	7,95

6.3.2 Deterministic Strategy: Energy + Capacity Optimization

Participation in the capacity market leads to a significant increase in total revenue. For a 2-hour battery, capacity payments amount to €86,280 per year, ensuring the battery's maximum overall revenue.

Table 7: Impact of battery duration on Deterministic Strategy: Energy + Capacity Optimization

Battery Size	Annual Revenue (EUR/MW-year)	Avg. Cycles/Day
1 MW / 4h	673,500	2.72
1 MW / 2h	646,752	5,34
1 MW / 1h	615,804	9,34

6.3.3 Heuristic Dynamic Bidding: Energy-Only Strategy

This case compares the revenue obtained when participation is limited to the energy auction; a larger-capacity battery allows higher revenue to be achieved while keeping cycles per day below 2.05. Table 14 and 15 show the best combinations for 1h and 4h battery.

Table 8: Impact of battery duration on Heuristic Dynamic Bidding: Energy-Only Strategy

Battery Size	Annual Revenue (EUR/MW-year)	Avg. Cycles/Day
1 MW / 4h	264,884	2.03
1 MW / 2h	190,464	2.04
1 MW / 1h	122.768	2.03

6.3.4 Static Capacity Sensitivity with Price Premiums

In Figures 28 and 29 it can be seen that, because all three cases share the same power rating, the capacity revenues are identical regardless of battery size. The 1-hour battery, however, incurs intraday costs at high capacity commitments in order to supply the energy required for capacity-market participation, whereas the 2-hour and 4-hour batteries face almost no such costs because they remain above the minimum energy threshold. Consequently, revenue differences arise from the extra cost of maintaining the energy needed for the capacity auction and from trading in the energy market.

Table 9: Impact of battery duration on Static Capacity Sensitivity with Price Premiums

Battery Size	Annual Revenue (EUR/MW-year)	Avg. Cycles/Day
1 MW / 4h	295,956	2.31
1 MW / 2h	219,084	3.00
1 MW / 1h	172,344	3,75

In Figure 7, the revenue from the various simulations is displayed together with the corresponding cycles-per-day values for each battery.

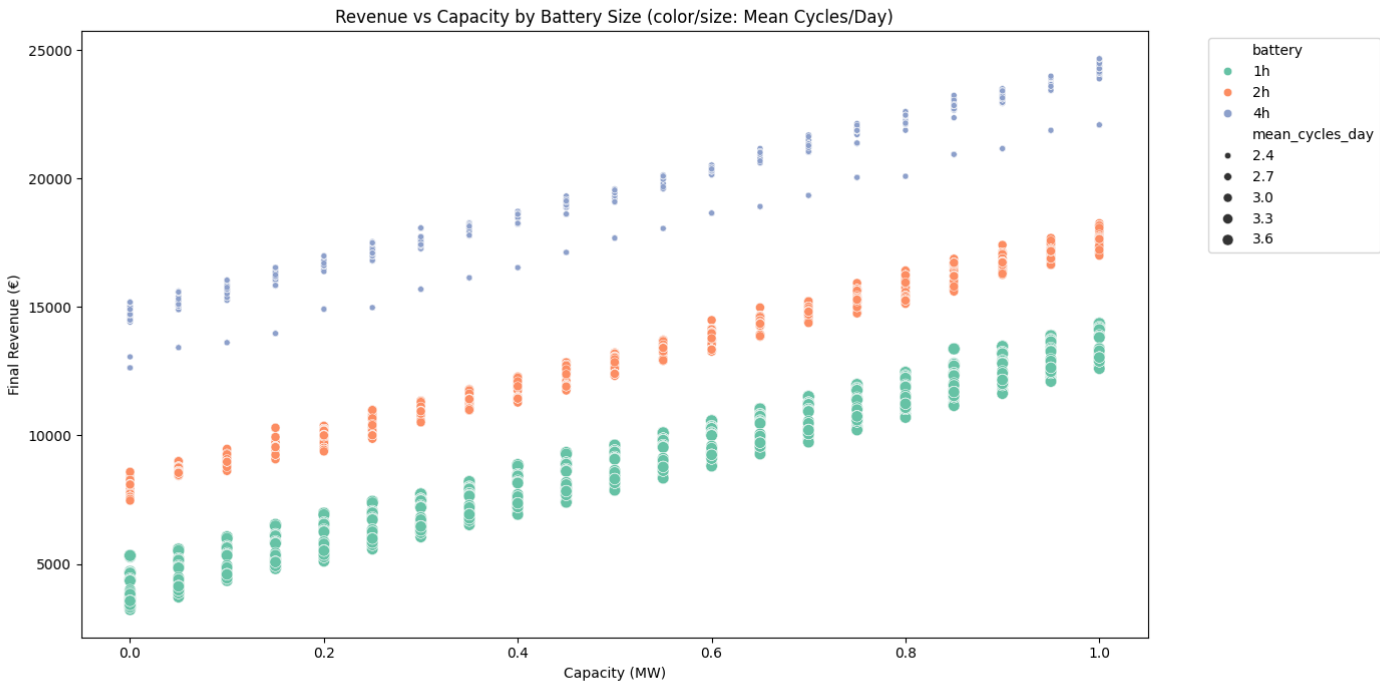


Figure 7: Weekly Revenue for capacity sensitivity analysis on Static Capacity Sensitivity with Price Premiums

6.3.5 Adaptive Strategy: Optimized Capacity and Price Premium Based on Previous 3 Days

Table 10: Impact of battery duration on Adaptive Strategy: Optimized Capacity and Price Premium Based on Previous 3 Days

Battery Size	Annual Revenue (EUR/MW-year)	Avg. Cycles/Day
1 MW / 4h	298,874	1.97
1 MW / 2h	223,596	2.10
1 MW / 1h	168,367	3,68

6.3.6 Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day

In every case the optimisation favours offering the battery's full capacity—1 MW—in the capacity auction for 92 % of the simulation period. This yields an identical €105 360 per year in all three scenarios, corresponding to 31.03 %, 47.97 %, and 60.45 % of total revenue for the 4-hour, 2-hour, and 1-hour batteries, respectively. Figure B.7 shows the detailed power and energy results for the batteries, together with the cycles-per-day control strategy.

Table 11: Impact of battery duration on Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day

Battery Size	Annual Revenue (EUR/MW-year)	Avg. Cycles/Day
1 MW / 4h	294,567	2,29
1 MW / 2h	219,596	2,95
1 MW / 1h	174,260	3.63

7 Day-Ahead Market Results

7.1 Overview and Objectives

This chapter presents the results of the regression analysis developed to identify the key drivers affecting the daily revenue of a battery operating in the Spanish Day-Ahead Market (DAH) between 2019 and 2025. The analysis is based on a multivariable linear regression model implemented in Python, as described in Sections 4.4 and 5.5.

The goal is to evaluate the explanatory power of market variables (such as electricity prices, fuel costs, and renewable generation) and technical metrics (such as battery cycling and installed capacity) on the simulated daily revenue of the battery. To assess model accuracy and robustness, the following steps were performed:

- Independent models were trained for each **season** and for each **calendar month** to capture temporal variability in market conditions.
- Model performance was evaluated using the **coefficient of determination** (R^2) and the **Mean Squared Error** (MSE) on test data.
- The most influential variables were identified based on the absolute value of their regression coefficients.

The results are organized into four sections. Section 7.2 presents the performance of the model by season, followed by monthly results in Section 7.3. Section 7.4 discusses the importance of individual variables. Finally, Section 7.5 provides a discussion of key insights and operational implications.

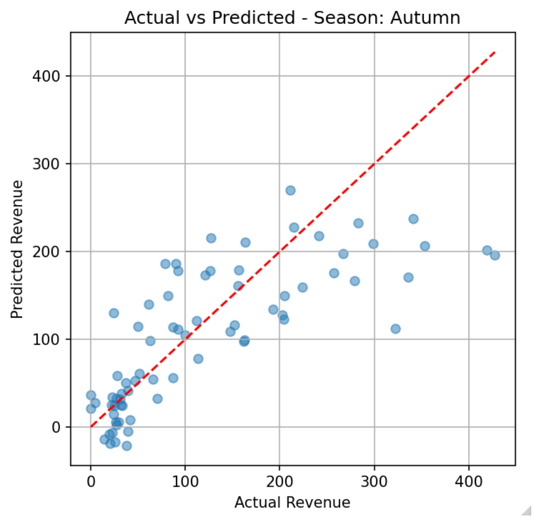
7.2 Model Performance by Season

To evaluate the ability of the regression model to capture seasonal effects, independent models were trained using grouped data for each of the four seasons: spring, summer, autumn, and winter. The performance was assessed using two standard metrics: the coefficient of determination (R^2) and the Mean Squared Error (MSE), both computed on the test set.

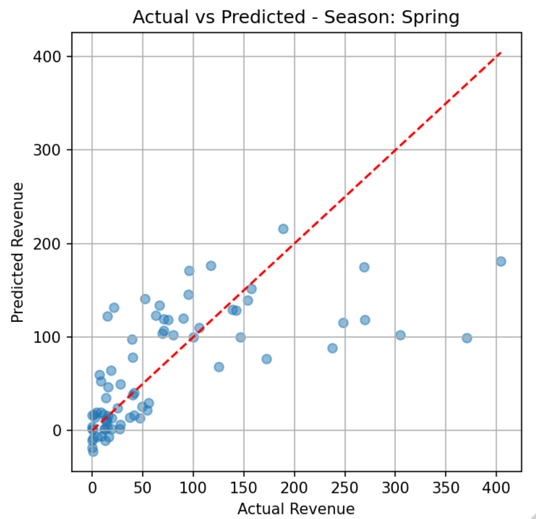
Figure 8 shows the scatter plots comparing predicted and actual daily revenues for each season. The visual dispersion provides a qualitative indication of the model's accuracy and robustness. As shown in the figure, summer presents the highest predictive performance, with data points closely aligned to the 45-degree line. In contrast, winter shows higher variance and reduced correlation, likely due to price volatility and a more complex interaction between variables.

The corresponding performance metrics are summarized in Table 12. The R^2 value for summer reaches 0.685, indicating a strong correlation between inputs and revenue. Meanwhile, the winter model produces a much lower R^2, suggesting that seasonal volatility and unobserved variables reduce the model's explanatory power during this period.

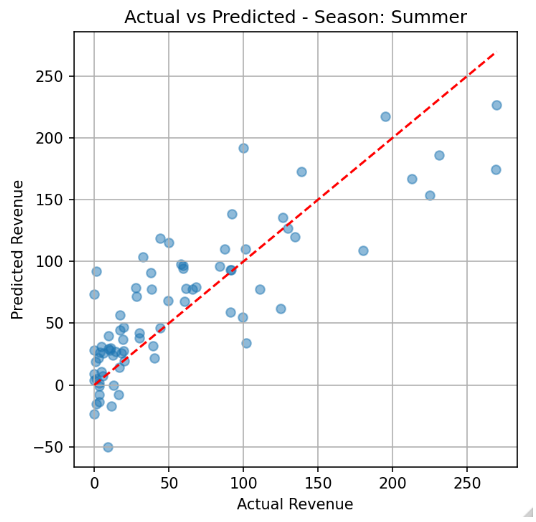
These results confirm that the model's ability to predict battery revenue is not constant throughout the year and is significantly affected by underlying seasonal market dynamics.



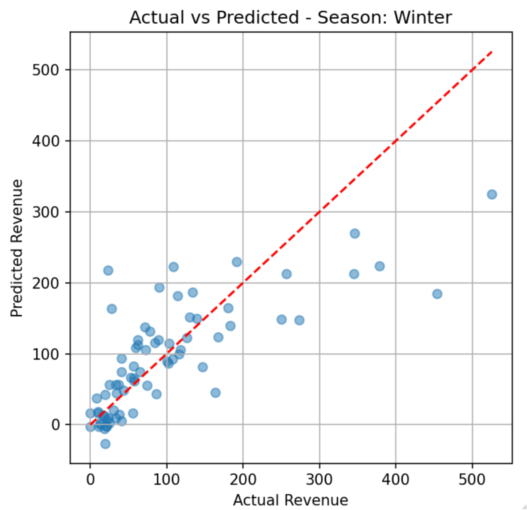
(a) Autumn — $R^2 = 0.567$, MSE $= 5090.07$ €^{2}



(b) Spring — $R^2 = 0.441$, MSE $= 4406.50$ €^{2}



(c) Summer — $R^2 = 0.685$, MSE $= 1365.56$ €^{2}

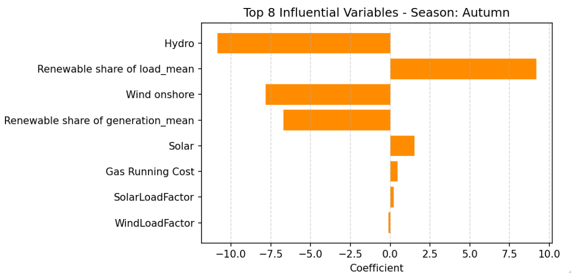


(d) Winter — $R^2 = 0.588$, MSE $= 4594.15$ €^{2}

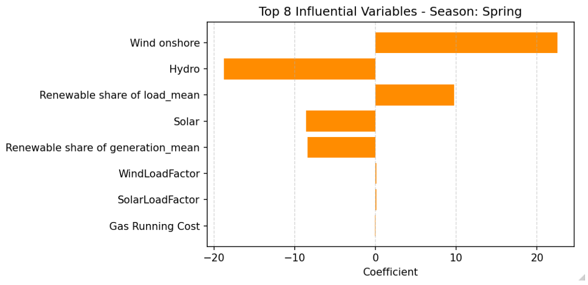
Figure 8: Predicted vs. actual daily revenue for each season.

Table 12: Regression model performance by season (test set).

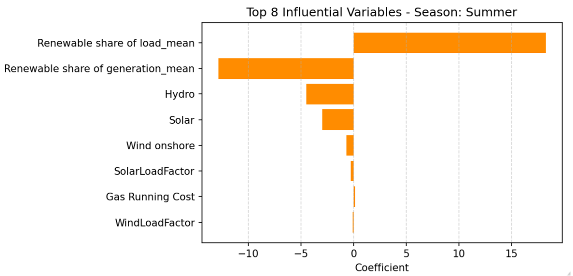
Season	R^2	**MSE**
Spring	0.441	4406.50 €^{2}
Summer	0.685	1365.56 €^{2}
Autumn	0.567	5090.07 €^{2}
Winter	0.588	4594.15 €^{2}



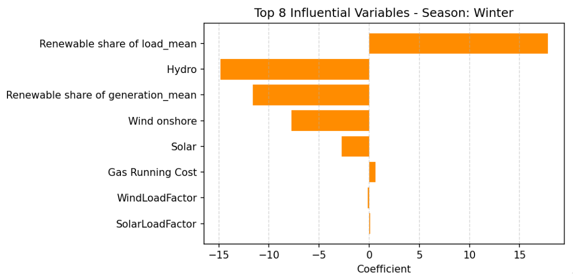
(a) Autumn



(b) Spring



(c) Summer



(d) Winter

Figure 9: Top regression coefficients by season. The coefficients are sorted by absolute value, showing the most influential variables on battery revenue for each period.

In the autumn model, the most influential variables include hydro capacity (negative), renewable share of load (positive), wind onshore capacity (negative), and renewable share of generation (negative). According to the figure: 9a

The negative coefficient of hydro capacity suggests that flexible hydro reduces price spreads by flattening daily price profiles, limiting arbitrage opportunities for batteries. The positive impact of renewable share of load likely reflects increased price volatility from intermittent sources like wind and solar. Conversely, the negative effect of wind onshore capacity may indicate that sustained wind output suppresses prices over long periods, reducing daily spread. Collinearity with other renewable related variables may also contribute to this outcome.

During the autumn season, the most influential variables were the installed hydro capacity (negative coefficient), the renewable share of load (positive), and installed wind onshore capacity (negative coefficient). This suggests that during wetter months, higher hydro availability may reduce the price volatility and thus limit arbitrage opportunities for the battery.

This interpretation aligns with official data from AEMET (Spanish State Meteorological Agency), [55] which identifies October and November as the rainiest months of the year 47. The regression results for these months (see Figures 45 and Table 18) show similar coefficient patterns to the autumn season model, supporting the idea that precipitation-related technologies like hydro play a significant role in shaping battery revenues during this period.

The model for the autumn season achieved an R^2 of 0.567 and a mean squared error (MSE) of

5090.07 €^{2}, indicating a moderate predictive capability. These results suggest that although the model captures relevant market and technical patterns, significant variability remains—possibly due to hydrological conditions and other weather-driven dynamics typical of October and November, which are statistically the rainiest months in Spain.

In the spring model, the most influential variable is the installed onshore wind capacity, with a strong positive coefficient. This suggests that wind generation plays a dominant role in driving battery revenues during this season. This is consistent with meteorological data, as April is typically the windiest month in Spain, allowing wind farms to produce at high output levels. This often leads to large intraday price swings—low prices during high wind periods and higher prices during lulls—creating profitable arbitrage opportunities for batteries.

The residual load also shows a positive coefficient, indicating that when renewable generation (mainly wind and solar) is not sufficient to cover demand, price volatility increases, boosting revenue potential. Meanwhile, the hydro capacity appears with a small negative coefficient, possibly reflecting that higher hydro availability reduces price variability by acting as a flexible resource in the system.

During summer, the most influential variable is the renewable share of load, showing a strong positive coefficient. This suggests that a higher penetration of renewables —especially solar—into the demand mix increases price volatility or spread, which enhances battery arbitrage revenue. This is consistent with seasonal generation patterns in Spain, where solar production peaks during the summer months.

In contrast, the renewable share of generation appears with a strong negative coefficient, likely capturing the effect of system-wide oversupply: as renewables dominate the generation mix (especially during midday hours), market prices may collapse across multiple hours, limiting the spread that batteries can exploit.

Additionally, hydro and solar installed capacities also exhibit negative coefficients. This might reflect that in periods with high renewable availability, price flattening occurs due to reduced residual load, reducing arbitrage opportunities. The impact of wind is negligible in summer, as expected, since wind speeds are relatively low during this season in most of Spain.

Among all seasonal models, summer achieves the highest predictive performance, with an R^2 of 0.685 and the lowest mean squared error (MSE = 1365.56 €^{2}). This suggests that the market dynamics during the summer months are more consistent and easier to capture through the selected input variables. The dominance of solar generation and clear renewable patterns in this season likely contribute to the model's improved accuracy compared to the more variable conditions of other seasons.

The winter model identifies the renewable share of load as the most influential variable, with a strong positive coefficient. This suggests that, even when renewables supply a significant portion of demand, price volatility may still increase during peak demand hours—such as cold evenings—when renewable output is insufficient. This dynamic creates larger intraday price spreads, which batteries can exploit through arbitrage.

Hydro capacity appears as the second most influential driver, with a large negative coefficient. This is consistent with seasonal conditions, as hydro availability typically peaks during the winter due to accumulated rainfall from autumn. The increased flexibility of hydro generation during these months tends to smooth price fluctuations, thereby limiting arbitrage opportunities for batteries.

Other variables such as the renewable share of generation and installed onshore wind capacity also show negative coefficients. These reflect periods of high renewable output, especially wind, that suppress electricity prices for extended hours. Although gas running costs show a minor positive effect—indicating that more expensive marginal generation can increase price peaks—overall price spreads remain dampened by the dominant presence of flexible and low-marginal-cost resources in the system.

7.3 Visual Insights and Correlation Analysis

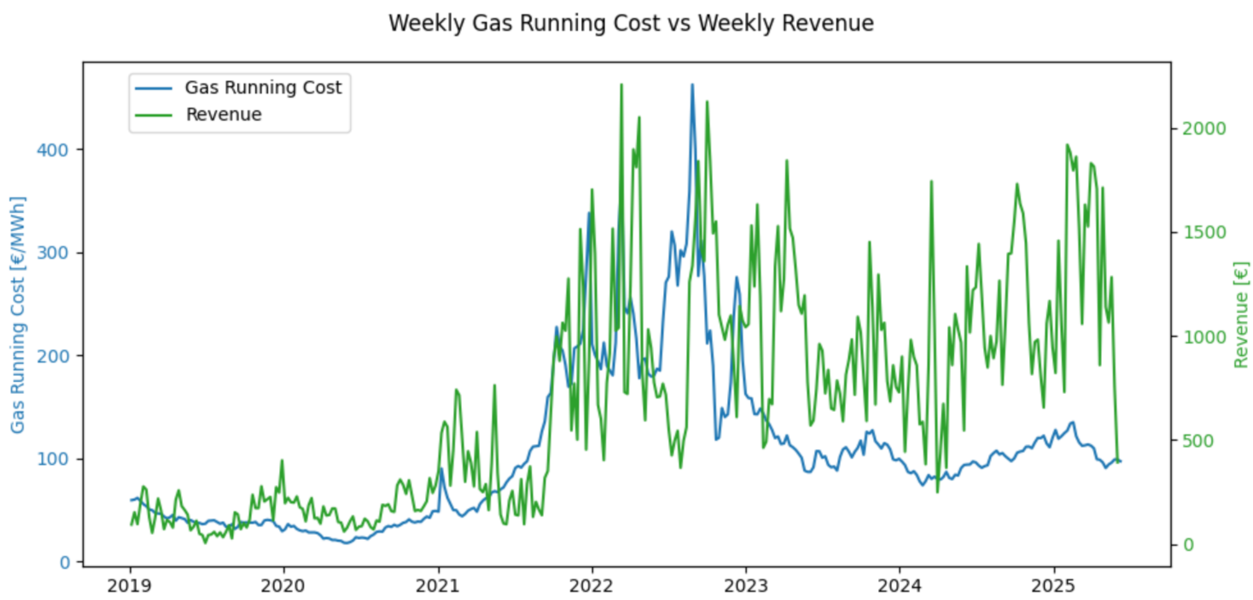


Figure 10: Correlation between the gas running cost and Battery revenue

Figure 10 presents the weekly evolution of gas running costs and simulated battery revenue between 2019 and 2025. A strong co-movement is observed during late 2021 and throughout 2022, where both variables peak simultaneously. This trend reflects a combination of geopolitical, structural, and market-specific dynamics that drastically increased price volatility.

Global Context. Beginning in the second half of 2021, European natural gas prices rose sharply due to:

- Low storage refill levels after the cold winter of 2020–2021,
- A strong post-COVID industrial rebound that increased energy demand,
- Reduced supply from Russia via the Nord Stream pipeline.

War in Ukraine. The Russian invasion of Ukraine in February 2022 intensified the crisis. Russia began progressively cutting gas flows to Europe, and gas prices—measured by the TTF index—reached historic highs. In response, many countries ramped up thermal generation. In marginal pricing markets like Spain, this led to extreme price peaks in the electricity market.

Spanish Market Implications. Spain operates under a marginal-cost pricing system, where the market clearing price is set by the most expensive unit (often gas-fired plants). As gas costs soared, electricity prices followed—especially during low-renewable hours. This created larger intraday spreads, directly increasing the revenue potential of battery energy storage systems through arbitrage.

Policy Reaction. Although the Spanish government introduced a gas price cap in June 2022 to dampen wholesale market prices, intraday volatility remained high. For batteries, this volatility translated into more profitable charging and discharging windows, as clearly reflected in the revenue spikes during 2022.

Indeed, as shown in the weights of the annual linear regression in Figure 41, the *Gas Running Cost* variable plays a significant role between 2019 and 2021. However, in 2022 it loses relevance, and in 2023 it regains notable influence. This trend is also reflected in the Pearson correlation coefficients shown in Table 19, where the coefficient for the maximum Gas Running Cost reaches values as high as 0.76 before 2022 and 0.60 in 2021. In contrast, in 2022 it drops to just 0.08, before rising again to around 0.30 in the following years. These results suggest that the increasing integration of renewable capacity into the system has weakened the dependence of battery revenue on gas running costs.

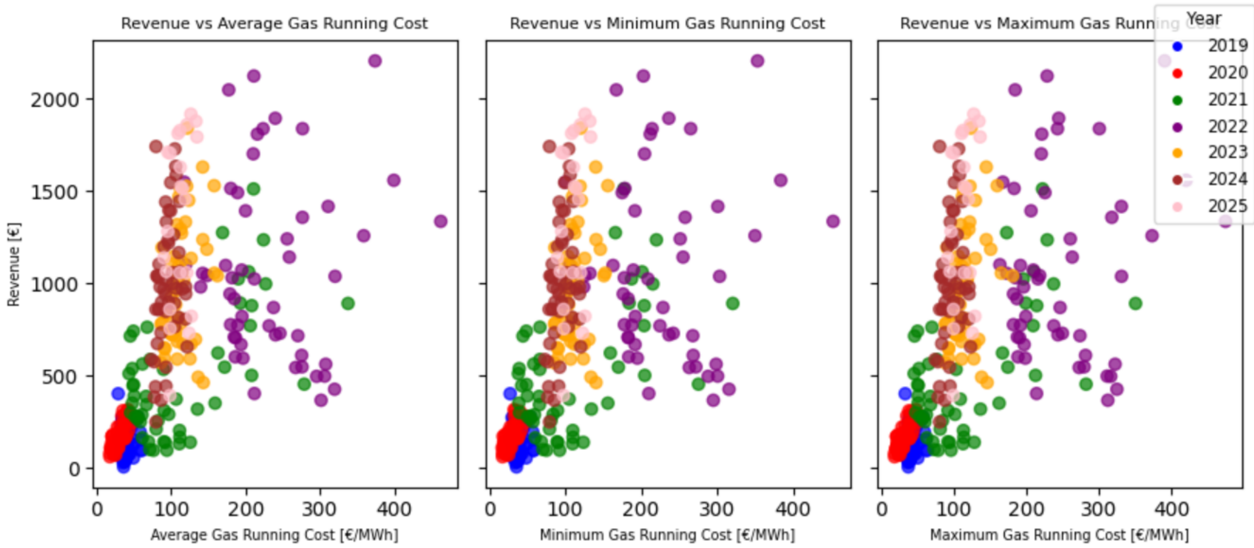


Figure 11: Correlation between the Battery Revenue and Gas Running Cost

In Figure 50, the linear relationship between gas and power price variables can be observed. Specifically, for the minimum power price, the gas cost often shows little relevance, as renewable sources and other technologies with lower marginal costs are frequently able to cover the full demand, thus setting the market price. However, a clearer linearity is observed in the relationship between the gas running cost and both the average and maximum power prices. As discussed previously, in Spain's marginal pricing system, the last technology to be dispatched determines the market price — and this is often a gas turbine. The model proposed by Centrica estimates potential battery revenue based on the spread in DAH market prices. Therefore, as shown in Figure 52, there is a visible linear trend between the maximum power price and battery revenue.

Residual load refers to the portion of electricity demand that remains after subtracting the generation covered by renewable sources. When this value is at its maximum, it indicates both a lower share of renewables and a higher total load. This typically occurs during late afternoon or evening hours, when solar generation drops to zero due to lack of irradiance and demand increases. As shown in Figure 54, the maximum residual load does not exhibit linearity with the minimum power price. However, it does show a clearer relationship with both the average and maximum prices, since when renewables are insufficient to meet demand, prices tend to rise depending on the marginal technology setting the market price.

As shown in Tables 22 and 23, there is a moderate negative correlation between average and minimum residual load and battery revenue during the years 2022 and 2023. This suggests that the battery performs better under conditions of high renewable generation (i.e., low residual load), when price volatility is typically higher. In contrast, the correlation between maximum residual load and battery revenue is weak or inconsistent across the years, indicating that revenue is not strongly influenced by peak demand periods but rather by the spread created when renewables displace more expensive generation sources during off-peak hours.

As shown in Table 24 and Figure 25, the correlation between total system load and battery revenue varies significantly across years. In 2020 and 2021, the correlations are weak and inconsistent, with both positive and negative signs depending on the load metric. However, in 2022, a strong negative correlation emerges, especially with minimum load ($r = -0.55$, $R^2 = 0.31$) and average load ($r = -0.50$, $R^2 = 0.25$).

This strong negative correlation in 2022 might be partially explained by the introduction of the Iberian gas price cap mechanism, implemented in June 2022. This policy decoupled the marginal electricity price from the full gas cost by capping the input fuel price used in thermal generation, thus introducing compensations in the market. As a result, price volatility increased—especially during periods of low load, typically with high renewable penetration—which could explain the stronger relationship between battery revenue and minimum/average load observed that year. From 2023 onwards, the negative correlation weakens again, which could suggest a rebalancing effect as the market adapted to the new price formation mechanism and as renewable penetration increased further.

8 Conclusions and Future Work

8.1 Optimal aFRR Trading Strategies and Their Impact on BESS Performance

- **Pricing-strategy control optimizes dispatch.** Introducing optimal up/down premiums (94 €/MWh up, 37 €/MWh down) in the energy-only heuristic raises annual energy revenue from € 177 812 to € 190 464 /MW-year (66% and 70% revenue of the benchmark) while reducing average cycles per day from 4.70 to 2.04. By filtering out low-margin activations, the battery is dispatched only during the most profitable intervals, improving both earnings and longevity.

- **Adaptive vs. constant capacity yields similar full-capacity exposure.**

  – A fixed 1 MW capacity bid achieves € 219 084/MW-year at 3.00 cycles/day, demonstrating the value of simple capacity participation.

  – The 3-day adaptive strategy elevates revenue to € 282 792/MW-year at just 1.13 cycles/day, capturing the majority of high-value periods with minimal cycling.

  – The hourly adaptive approach yields € 219 596/MW-year at 2.95 cycles/day—almost identical to the static case.

  In all cases, over 90% of time steps see full-capacity (1 MW) offers in the capacity auction, indicating that both adaptive and static strategies naturally converge on maximum-capacity bidding under prevailing aFRR price conditions.

- **Lack of daily price pattern** The superior performance of the 3-day look-back over the hourly look-back—despite its coarser temporal resolution—suggests that aFRR prices lack a consistent hourly pattern that can be exploited. Instead, leveraging recent multi-day trends provides a more robust basis for setting capacity and price premiums, balancing revenue capture with cycle-life constraints.

- **Sensitivity analysis** The sensitivity analysis confirms that battery duration is a critical driver of both revenue and cycling behavior, fully addressing our objective to assess key parameter impacts. Increasing storage from 1 h to 4 h raises annual revenues by roughly 27 % for energy-only strategies (from €238 k to €303 k) while cutting average daily cycles from 8 to 2. Combined energy–capacity optimization sees diminishing returns beyond 2 h (9 % gain to €647 k at 2 h vs. 4.7 % to €673 k at 4 h), and dynamic bidding/pricing strategies exhibit modest elasticity (<5 % uplift from 2 h to 4 h). Thus, a 2 h battery duration strikes an optimal balance—capturing 66 %–96 % of the perfect-foresight benchmark across strategies with a moderate 2–5 daily cycles—demonstrating how sizing decisions are as pivotal as bidding approaches.

8.2 Revenue Drivers and Seasonal Dynamics in the Day-Ahead Market

It can be observed that revenue depends strongly on price volatility and spreads. Gas running cost and CO price also play key roles: gas running cost's R^2 peaked at 0.76 before 2022, collapsed to 0.08 in 2022 under Spain's price cap, then recovered to 0.30 by 2024, mirroring the effect of regulatory caps on spreads. Abundant hydro output smooths prices and limits arbitrage value. In the spring, hydroelectric power has a minor negative coefficient, and in the winter, it is the second most influential driver with a high negative coefficient.

A correlation analysis over 2022–23 shows a moderate negative relationship between average residual load and battery revenue (e.g. $R = -0.3277$, $R^2 = 0.1074$ in 2022), implying that when total renewable output—especially hydro—is low, dawn and early-morning price spreads widen and boost arbitrage value.

During spring, onshore wind capacity is the strongest positive driver (April's high winds), while hydro capacity carries a small negative coefficient, indicating that spring runoff smooths out price swings. During Summer, solar's share of load leads as the main positive driver—midday spreads peak under intense sun—whereas abundant hydro and wind generation dampen those spreads, reflected in their negative coefficients. During winter Hydro capacity again has a pronounced negative effect on spreads (thanks to autumn–winter inflows), while the renewables-share remains a positive driver because low solar and variable wind extend and deepen peak spreads.

8.2.1 Future Outlook: Integrated Strategies Market Participation

In future research, the following extensions and enhancements are planned:

- **Geographical expansion:** Extend the framework to additional countries (e.g. France, Germany, Nordics) to compare aFRR and DAH price dynamics, market rules and regulatory caps across different jurisdictions.
- **Multi-market stacking:** Incorporate other flexibility markets (e.g. mFRR, FCR) and develop co-optimization routines to stack revenue streams by simultaneously bidding energy and capacity across multiple products.
- **Curtailment scenarios:** Model expected future curtailment constraints—driven by high renewable penetration—and simulate their impact on BESS dispatch and revenue capture.
- **Revenue forecasting:** Build a scenario-based revenue forecaster using stochastic methods to quantify expected returns under varying price volatilities scenarios, regulatory changes and technology cost curves.
- **Battery degradation modeling:** Integrate cycle-based aging models to explicitly trade off short-term revenue versus long-term capacity fade, optimizing bid strategies for total lifecycle value.
- **Advanced price and load forecasting:** Leverage machine-learning techniques (e.g. random forests, LSTM networks) to improve short-term price and residual-load forecasts, feeding more accurate signals into our adaptive bidding algorithms.

9 Alignment with Sustainable Development Goals (SDGs)

The Sustainable Development Goals (SDGs) are a set of 17 targets adopted by all United Nations Member States in 2015. [56] This set of targets encompasses a wide range of challenges, from ending poverty, inequality, relieving and minimizing the consequences of climate change, environmental degradation, peace among nations, and justice among others.

Some of the SDGs are addressed in this project.

- **7 Ensure access to affordable, reliable, sustainable and modern energy for all.** As we highlighted the strategy of the European Commission is to reach an integrated Electricity Market to protect the security of supply with a mostly renewable sources.
- **9 Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation.** We are fostering indirectly the BESS systems innovation as the sustainable energy supply
- **13 Take urgent action to combat climate change and its impacts** Thanks to the renewable energy we could mitigate the climate change consequences and reach the targets set by the European Commission

Figure 12: Sustainable Development Goals (SDGs

A Complementary Theoretical Foundations

A.1 Grid Converters

The integration of Battery Energy Storage Systems (BESS) into the electric grid is enabled by power electronic converters, which interface the DC output of the batteries with the AC grid. These converters play a critical role not only in energy exchange but also in providing fast-acting ancillary services that support grid stability in the absence of traditional synchronous inertia [51],[57].
The most commonly used converters in BESS applications are:

- **Two-Level Voltage Source Inverters (VSI)**: These are widely used in small and medium-scale applications. They use pulse-width modulation (PWM) to generate AC waveforms and offer high switching frequency but suffer from increased switching losses.
- **Multilevel Inverters (MLI)**: Including Neutral-Point Clamped (NPC) and Cascaded H-Bridge topologies. These are better suited for medium- and high-voltage applications due to reduced harmonic distortion and higher efficiency.
- **Bidirectional Converters**: These allow for both charging and discharging of the battery and typically consist of a DC-DC converter (for state-of-charge control) and a DC-AC inverter (for grid interaction) [58].

These converters rely on advanced control schemes to provide grid support functionalities. The three most relevant strategies include:

- **Virtual Synchronous Machine (VSM)**: This approach mathematically emulates the dynamic behavior of synchronous generators, including inertia and damping, through software control of the inverter. VSMs improve transient stability and synchronization with the grid by implementing swing equations internally [26].
- **Droop Control**: Based on frequency-power and voltage-reactive power relationships, this decentralized strategy allows multiple BESS units to share load without direct communication. It is particularly useful in microgrids or distributed systems and mimics the load-sharing behavior of synchronous machines [58].
- **Synthetic Inertia (Fast Frequency Response)**: This method provides a rapid response to frequency deviations by detecting the rate of change of frequency (RoCoF) and injecting active power accordingly. It acts within milliseconds and is highly effective in preventing frequency collapse but requires precise tuning to avoid oscillations [26].

From a regulatory perspective, Germany is currently discussing opening its markets to allow BESS to provide inertia-related services and is considering reforms to grid tariffs to reflect the system value of these resources [28]. Such developments suggest an evolving recognition of the strategic role of battery-based converters in maintaining system reliability in low-inertia grids.

Table 13: Comparison of Converter Control Strategies in BESS

Control Strategy	**Response Time**	**Nature**	**Gen. Model**	**Typical Application**
Virtual Synchronous Machine	Slow–medium	Physical-like	Yes	Transmission-level grid integration
Droop Control	Medium	Emulated	No	Microgrids, distributed coordination
Synthetic Inertia	Fast (ms)	Reactive	No	Fast Frequency Response (FFR)

B aFRR Analysis

B.1 Data Input

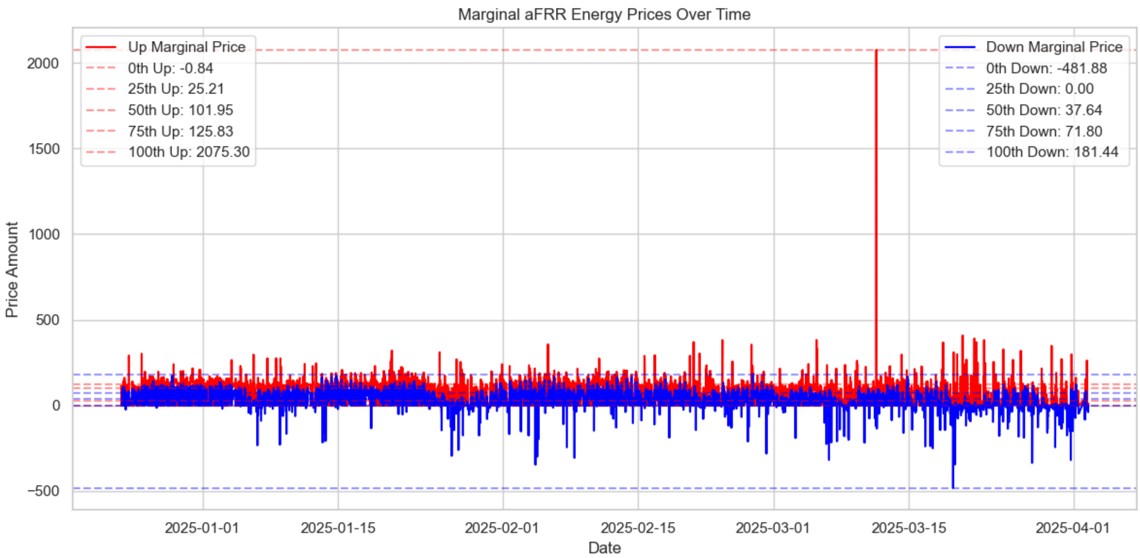


Figure 13: Marginal Energy aFRR Prices(€^{2}/MWh) Over Time with Percentiles

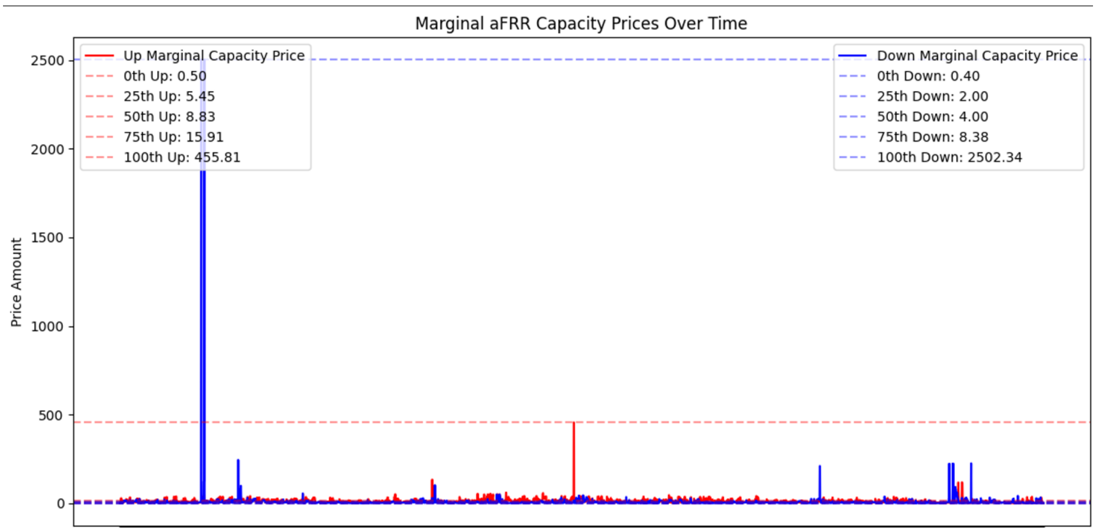


Figure 14: Marginal Capacity aFRR prices (€^{2}/MW) over time with percentiles.

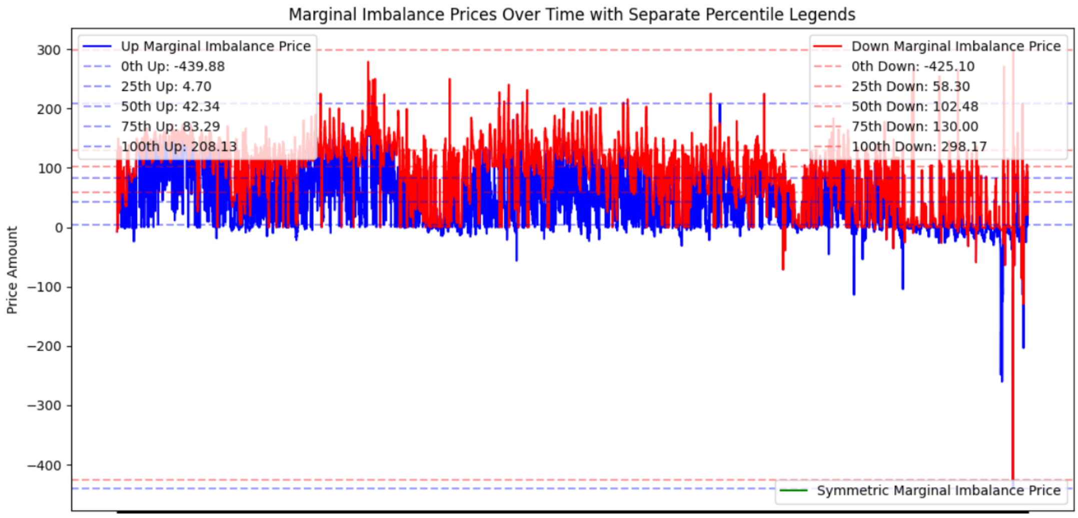


Figure 15: Intraday prices (€^{2}/MWh) over time with percentiles.

B.2 aFRR Trading Strategies

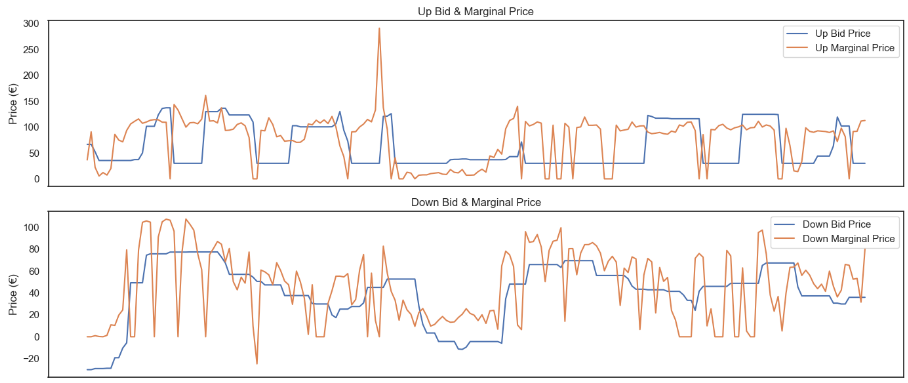


Figure 16: Pricing Strategy for upward and downward bids ((€^{2}/MWh)) with Up Premium = 50 y Dn Premium = 50

B.2.1 Deterministic Strategy: Energy-Only Optimization

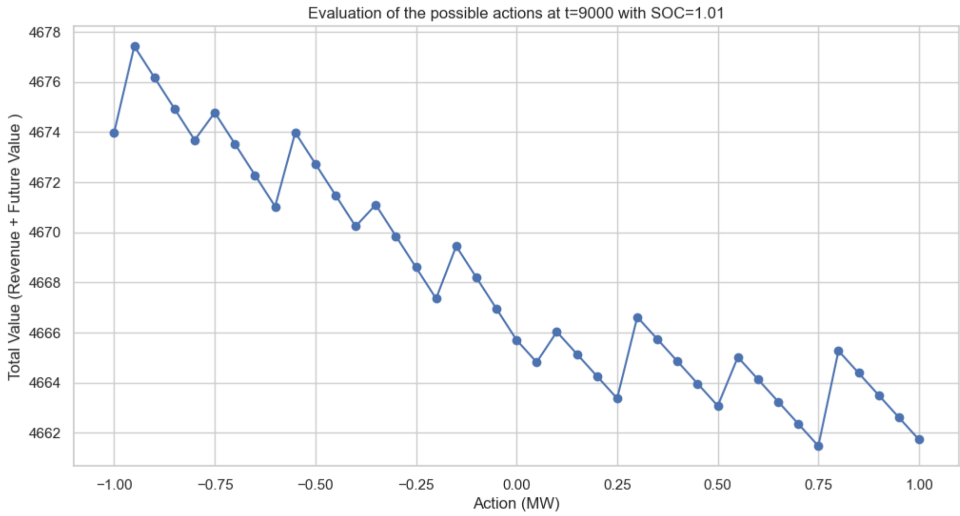


Figure 17: Evaluation of total value (immediate revenue plus future value) for all possible actions at time step $t = 9000$, given a state of charge (SOC) of 1.01. The action space corresponds to discrete power setpoints ranging from full discharge (-1 MW) to full charge (+1 MW). This plot illustrates how the dynamic programming algorithm assesses the optimal decision at a given state.

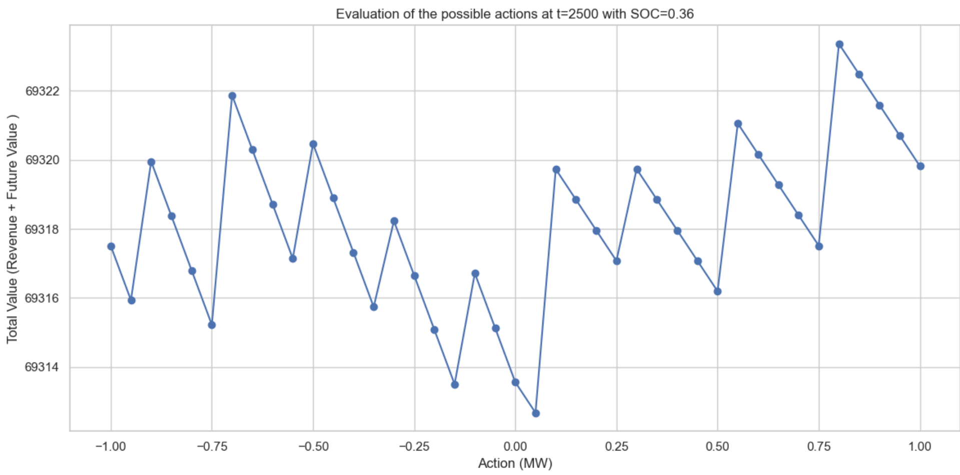


Figure 18: Evaluation of total value (immediate revenue plus future value) for all possible actions at time step $t = 2500$, given a state of charge (SOC) of 0.36. The action space corresponds to discrete power setpoints ranging from full discharge (-1 MW) to full charge (+1 MW). This plot illustrates how the dynamic programming algorithm assesses the optimal decision at a given state.

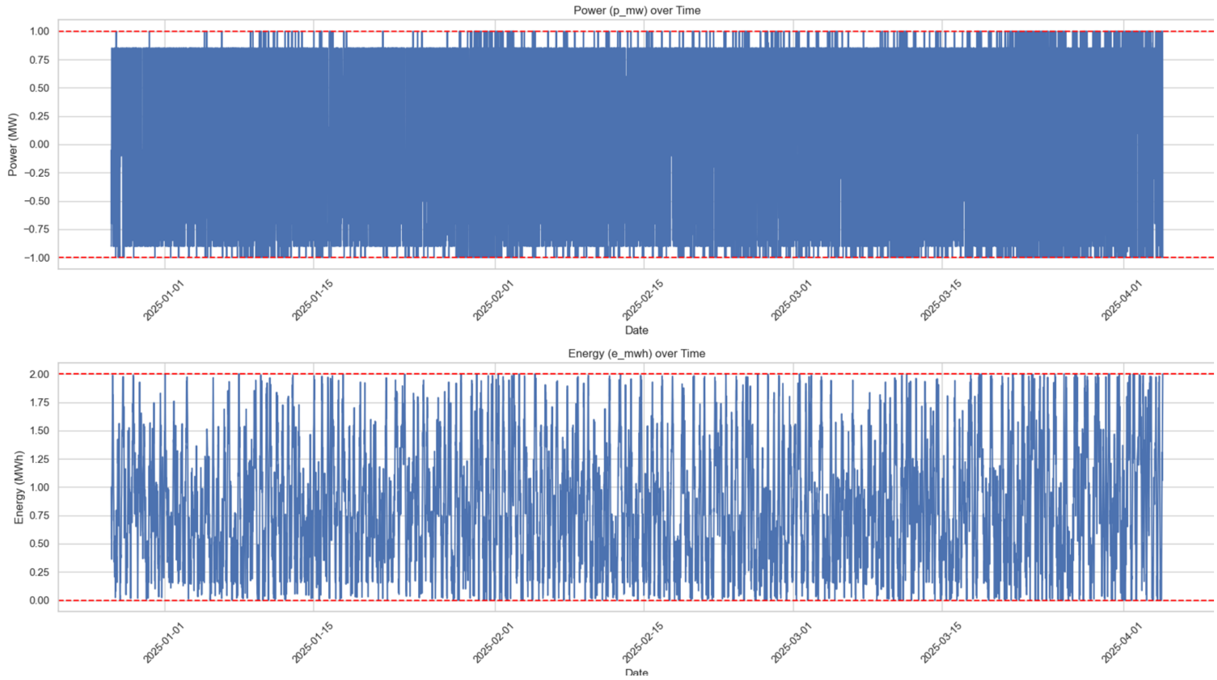


Figure 19: Power and Energy in the Deterministic Strategy: Energy-Only Optimization for 2h Battery

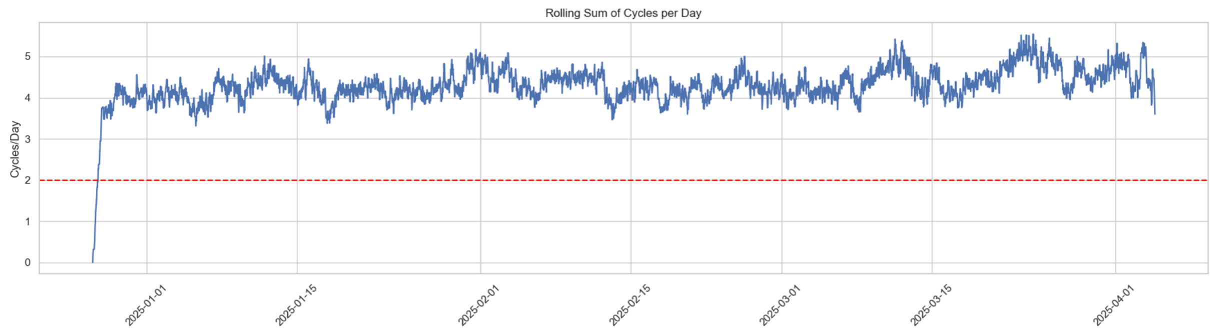


Figure 20: Cycles per day in the Deterministic Strategy: Energy-Only Optimization for 2h Battery

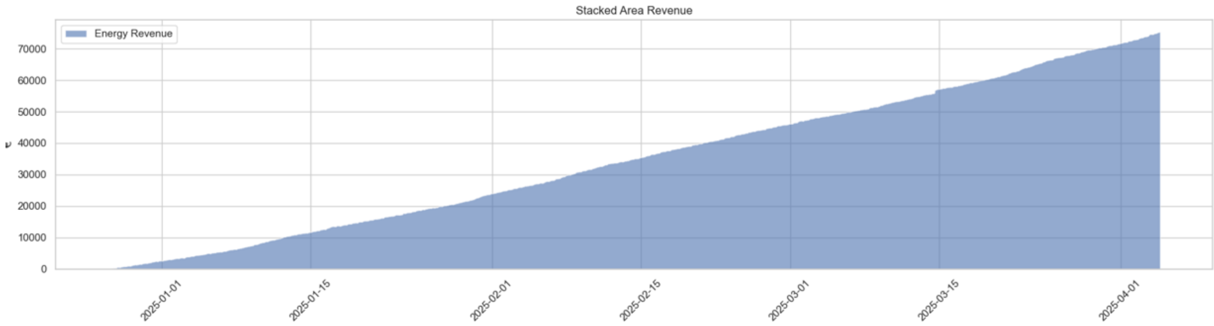


Figure 21: Energy Revenue in the Deterministic Strategy: Energy-Only Optimization for 2h Battery

B.3 Deterministic Strategy: Energy + Capacity Optimization

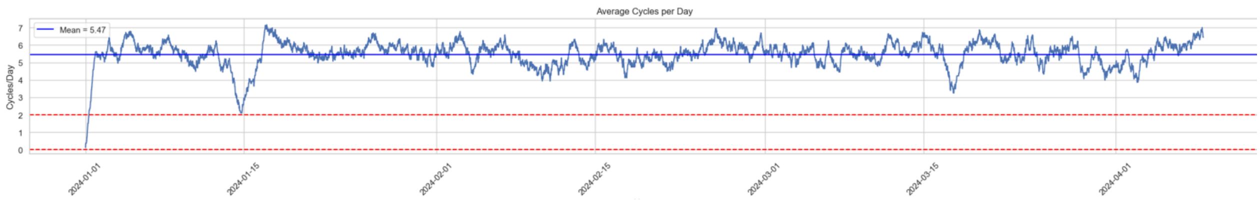


Figure 22: Cycles per day in the Deterministic Strategy: Energy + Capacity Optimization for 2h Battery

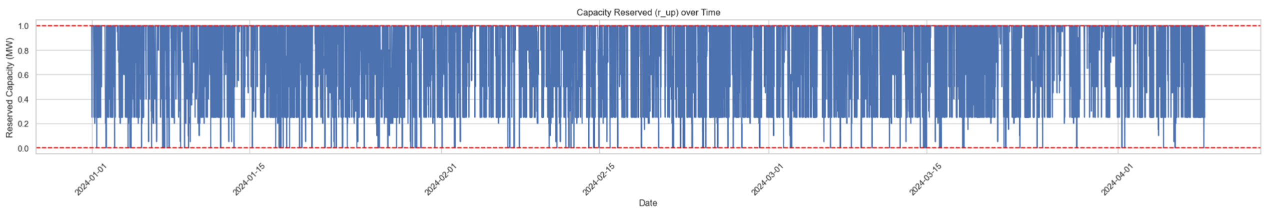


Figure 23: Reserved Capacity in the Deterministic Strategy: Energy + Capacity Optimization for 2h Battery

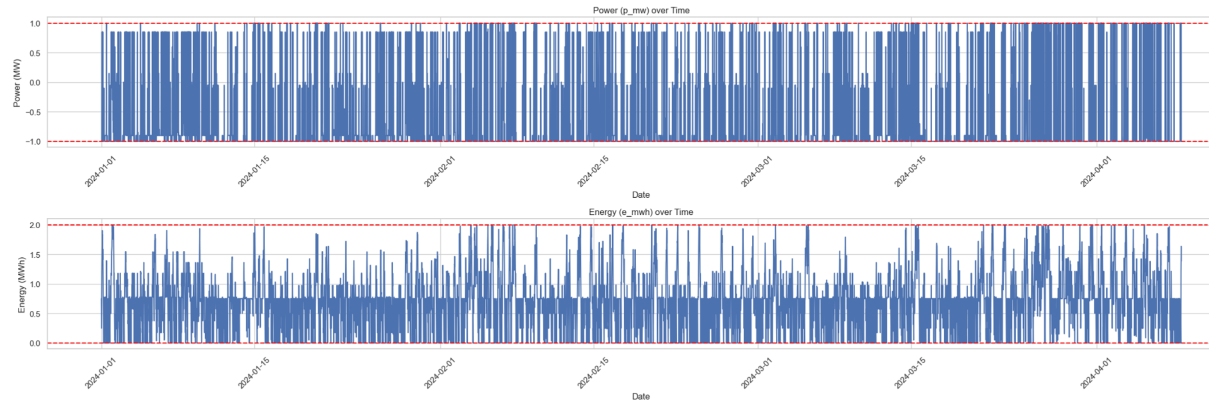


Figure 24: Power and Energy in the Deterministic Strategy: Energy + Capacity Optimization for 2h Battery

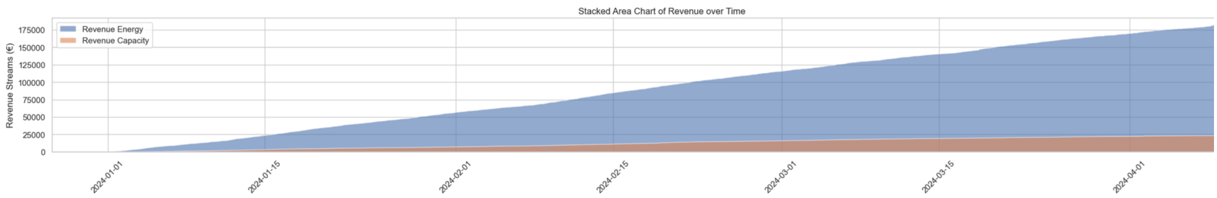


Figure 25: Energy and Capacity Revenue in the Deterministic Strategy: Energy + Capacity Optimization for 2h Battery

B.4 Heuristic Dynamic Bidding – Energy-Only Strategy

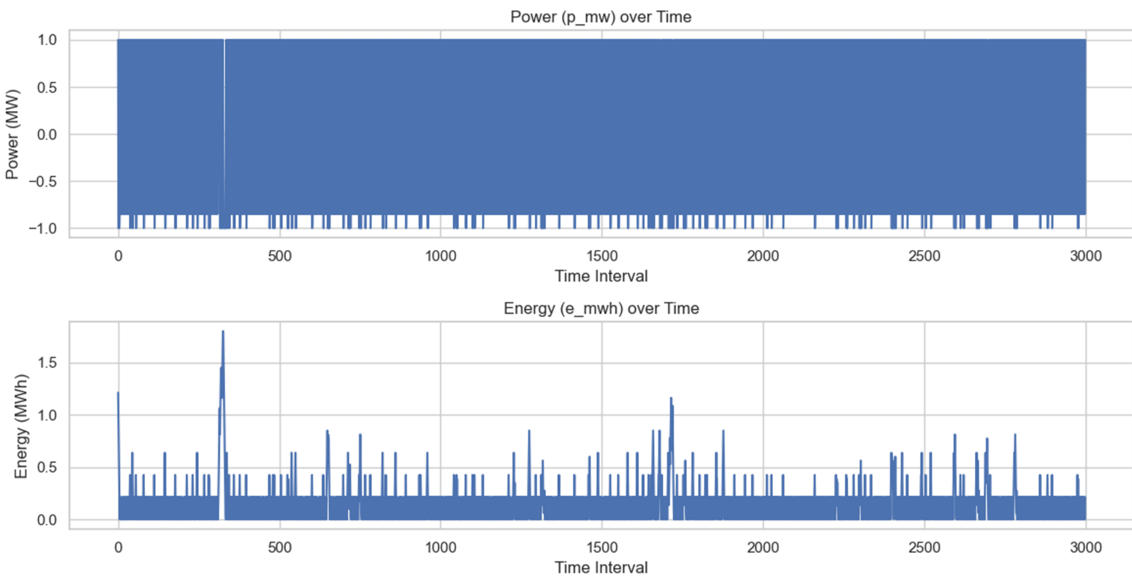


Figure 26: Operational Variables Power(MW) and Energy(MWh) in the Energy Bidding Strategy with no Premiums

Table 14: Top 10 premium combinations ranked by mean cycles per day and annual revenue (4h battery).

Up Premium (€/MWh)	Down Premium (€/MWh)	Mean Cycles/Day	Annual Revenue (€/MW)
21	0	2.367	279,378.52
22	0	2.362	279,283.20
17	0	2.396	278,868.16
20	0	2.375	278,442.08
19	0	2.383	278,386.00
24	0	2.344	277,845.12
15	0	2.414	277,796.72
18	0	2.388	277,765.84
16	0	2.406	277,764.44
23	0	2.352	277,658.00

Table 15: Top 10 premium combinations ranked by mean cycles per day and annual revenue under 2.05 cycles per day (1 hour battery).

Up Premium (€/MWh)	Down Premium (€/MWh)	Mean Cycles/Day	Annual Revenue (€/MW)
99	67	2.034	122,770.64
98	67	2.036	122,650.96
97	67	2.045	122,608.96
96	67	2.047	122,198.16
95	67	2.049	121,950.28
99	68	1.987	120,800.52
98	68	1.985	120,524.80
97	68	1.992	120,281.56
96	68	1.994	119,858.60
95	68	1.998	119,810.52

B.5 Static Capacity Sensitivity with Price Premiums

Table 16: Top 10 premium combinations for Battery 2 ranked by final annual revenue and 1MW fixed in the capacity market

Up Premium (€/MWh)	Down Premium (€/MWh)	Mean Cycles/Day	Annual Revenue (€/MW-year)
1	0	3.004	219 091.25
1	1	2.999	218 091.37
1	3	2.999	218 091.37
1	7	2.999	218 091.37
1	5	2.999	218 091.37
1	2	2.999	218 091.37
1	6	2.999	218 091.37
1	4	2.999	218 091.37
3	0	3.002	216 977.17
2	0	3.004	215 452.47

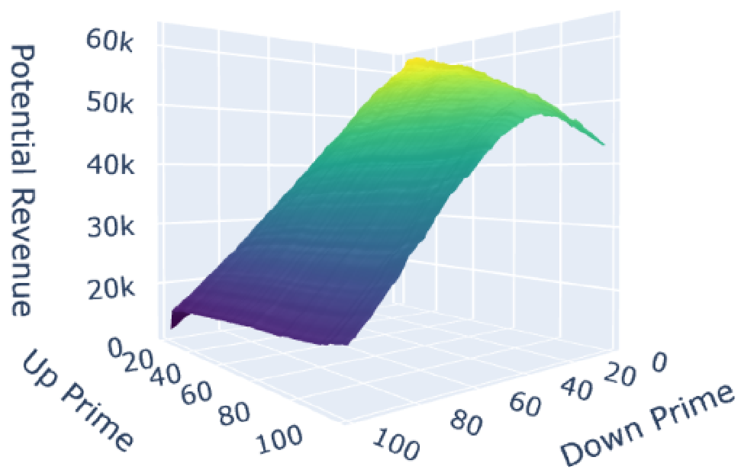


Figure 27: 3D Revenue (€/3months) sensitivity Analysis in Heuristic Dynamic Bidding – Energy-Only Strategy for a 2h battery

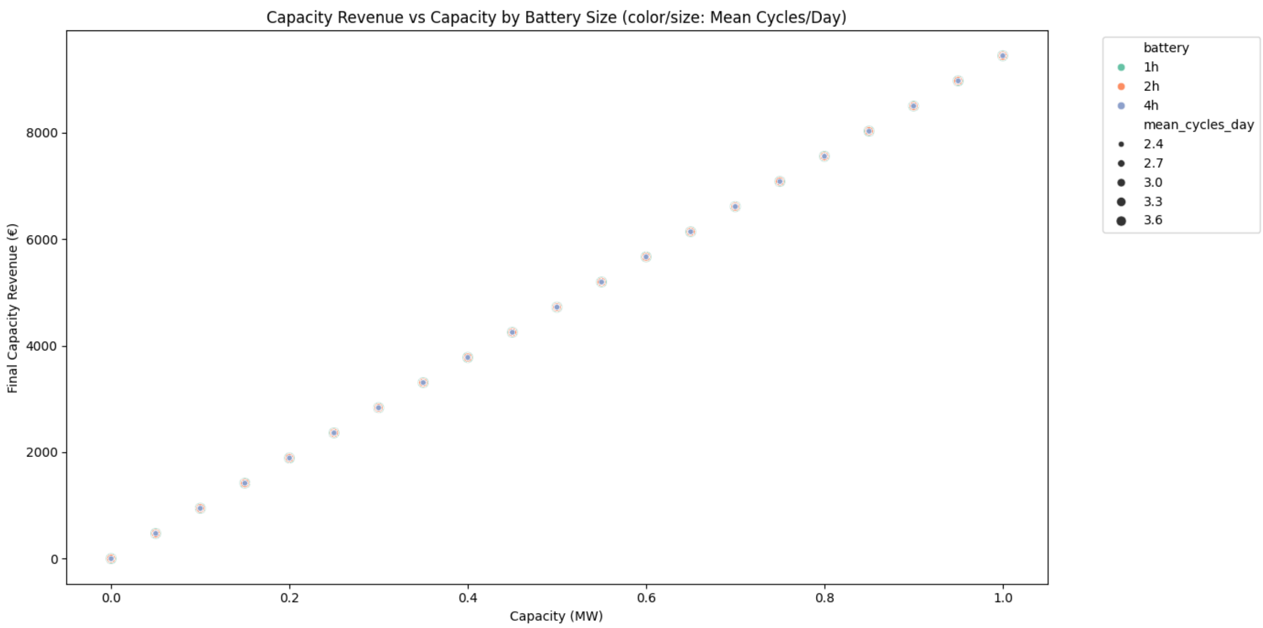


Figure 28: Weekly Capacity Revenue for sensitivity analysis on Static Capacity Sensitivity with Price Premiums

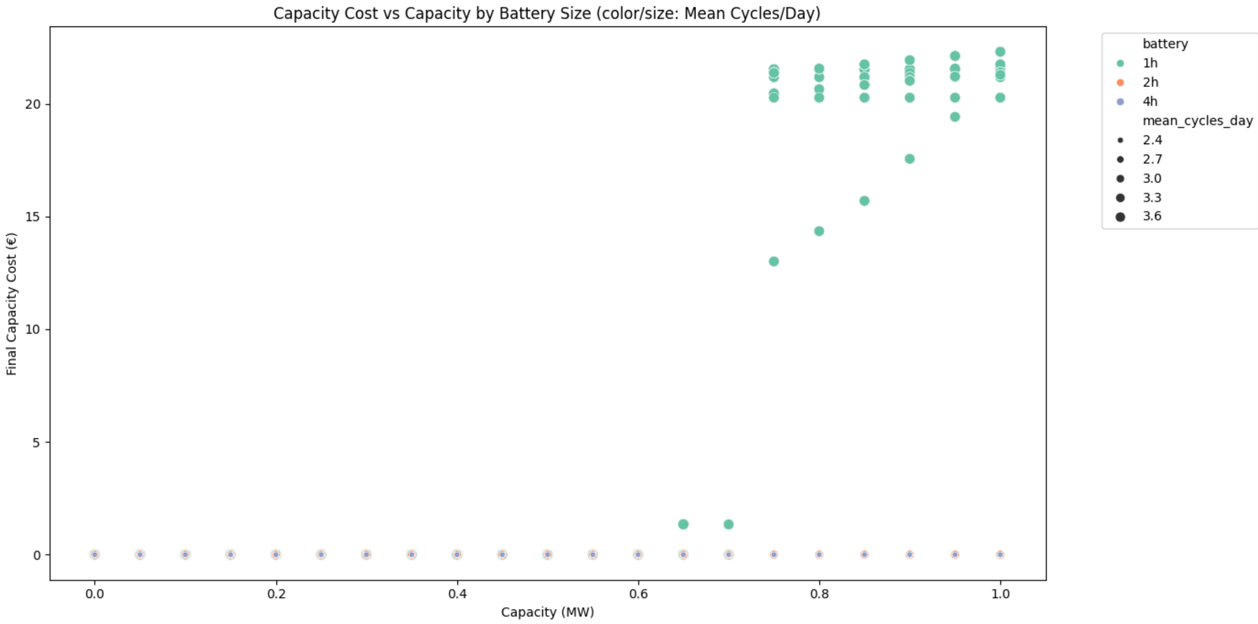


Figure 29: Weekly Capacity Cost for sensitivity analysis on Static Capacity Sensitivity with Price Premiums

B.6 Adaptive Strategy: Optimized Capacity and Price Premium Based on Previous 3 Days

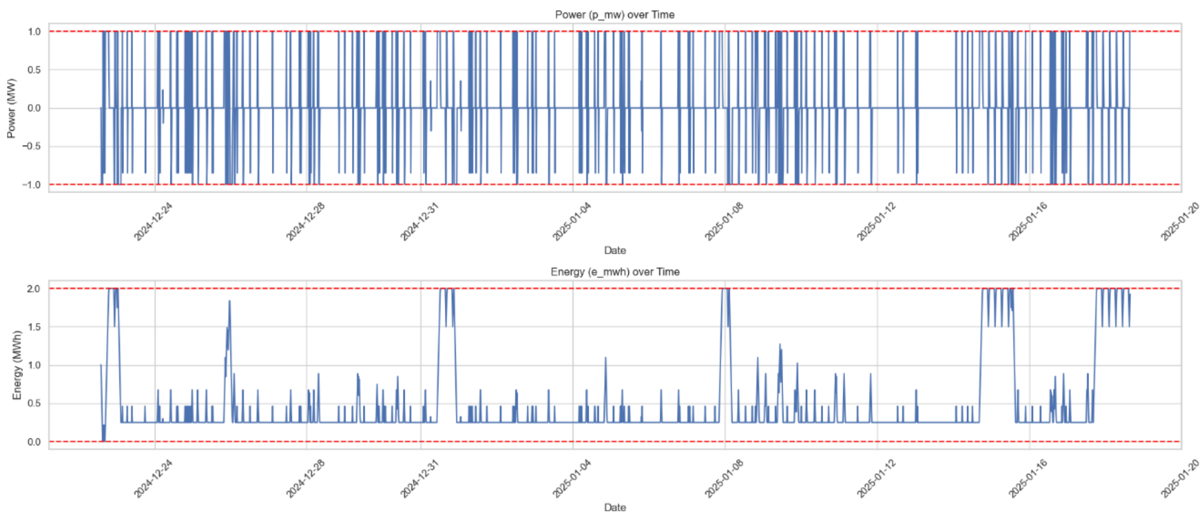


Figure 30: Power and Energy in the Adaptive Strategy: Optimized Capacity and Price Premium Based on Previous 3 Days for 2h Battery

Figure 32: UP/DN Premiums in the Capacity Auction in the Adaptive Strategy: Optimized Capacity and Price Premium Based on Previous 3 Days for 2h Battery

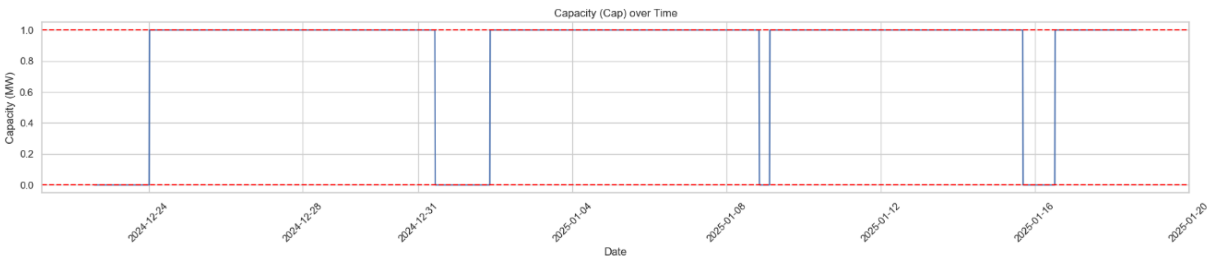


Figure 31: Capacity Traded in the Capacity Auction in the Adaptive Strategy: Optimized Capacity and Price Premium Based on Previous 3 Days for 2h Battery

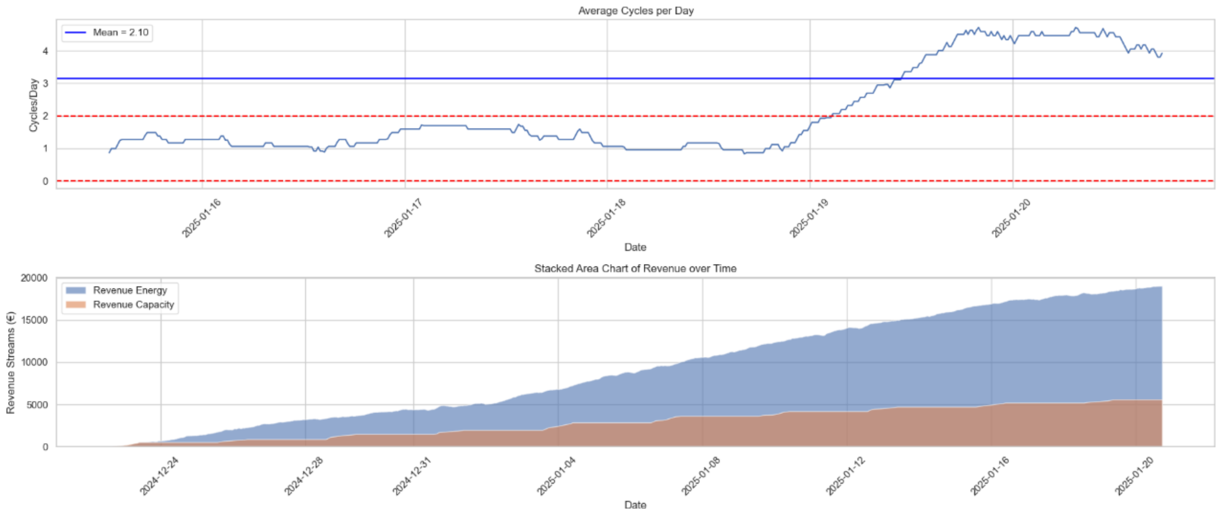


Figure 33: Monthly Revenue and Cycles per Day n the Capacity Auction in the Adaptive Strategy: Optimized Capacity and Price Premium Based on Previous 3 Days for 2h Battery

B.7 Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day

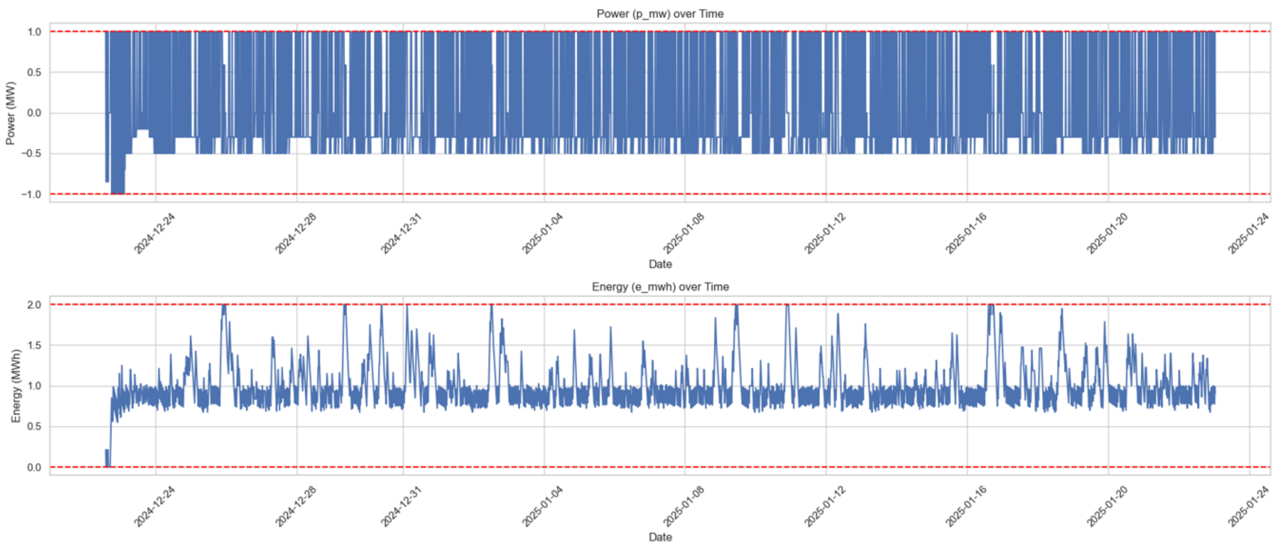


Figure 34: Power and Energy in the Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day for 2h Battery

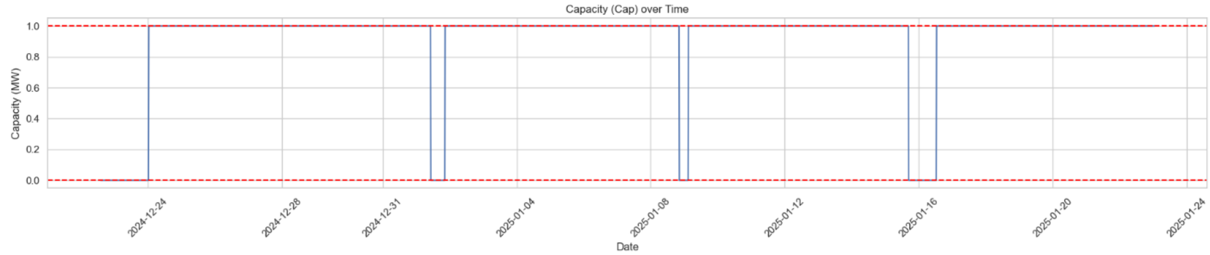


Figure 35: Capacity Traded in the Capacity Auction in the Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day for 2h Battery

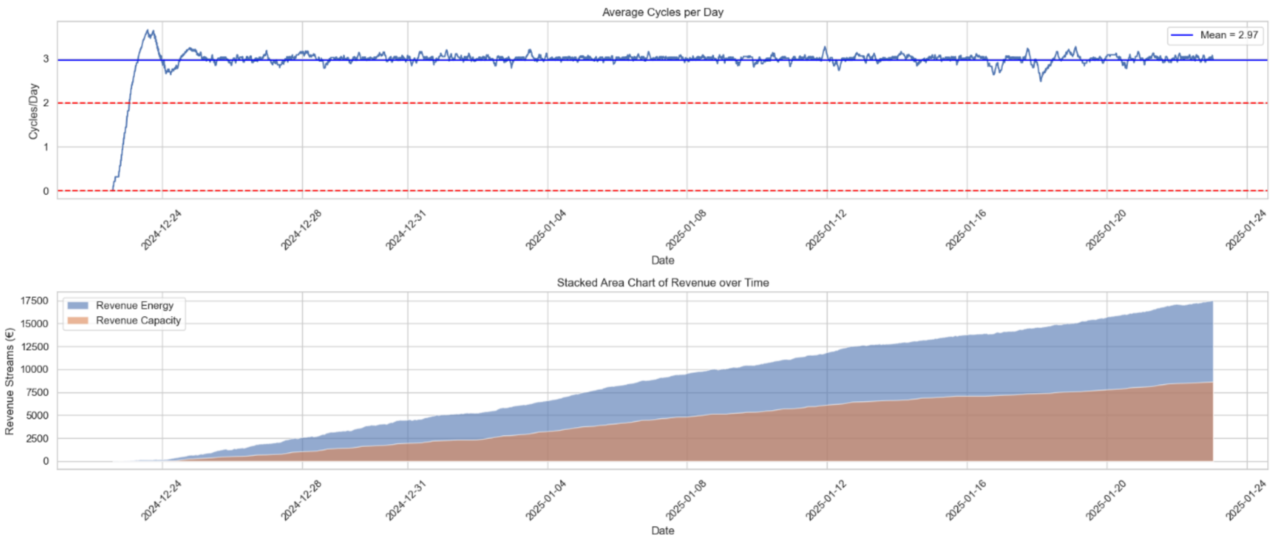


Figure 36: Cycles per day and Revenue in the Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day for 2h Battery

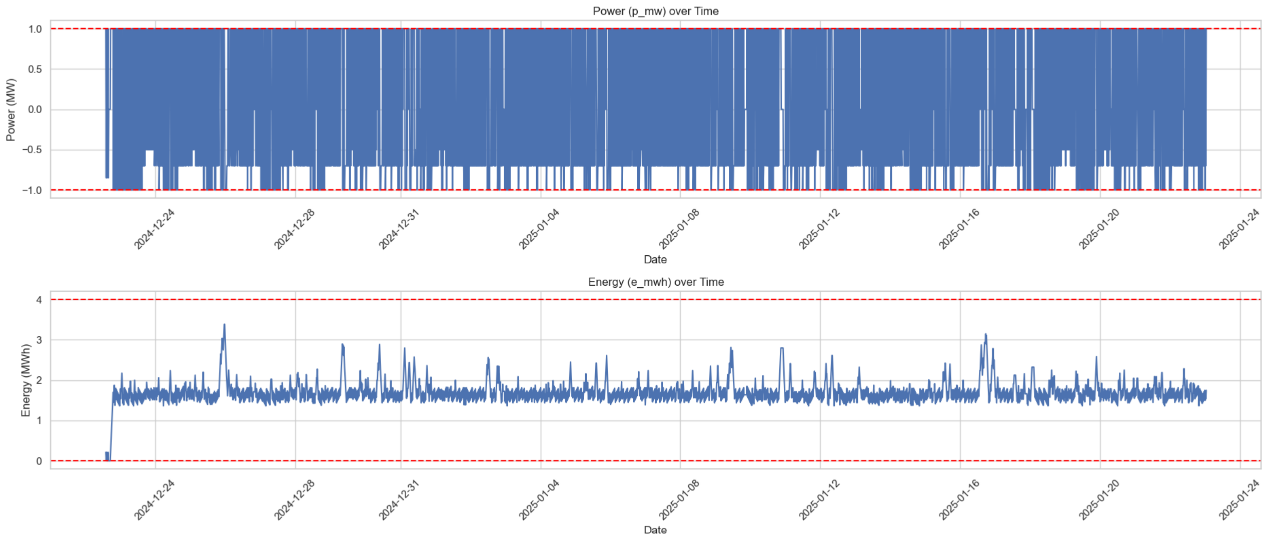


Figure 37: Power and Energy in the Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day for 4h Battery

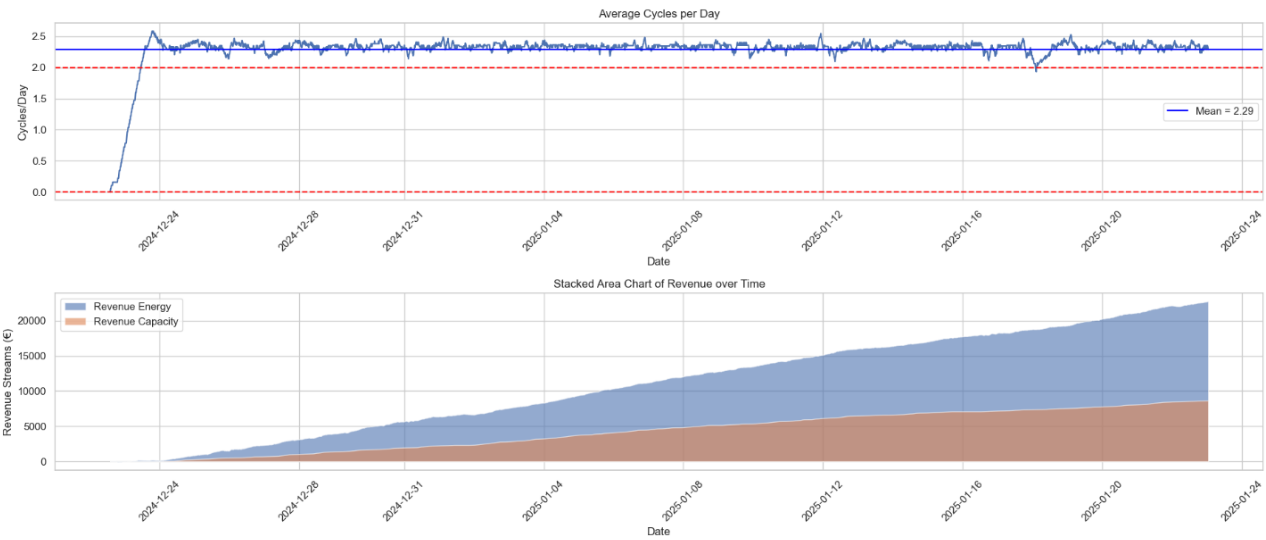


Figure 38: Cycles per day and Revenue in the Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day for 4h Battery

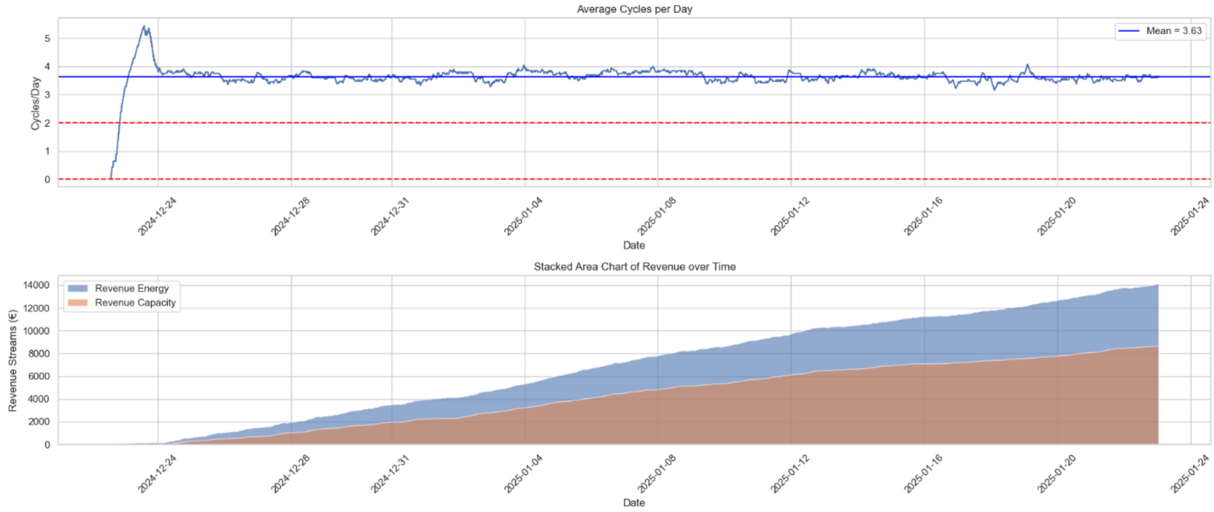


Figure 39: Cycles per Day and Revenue in the Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day for 1h Battery

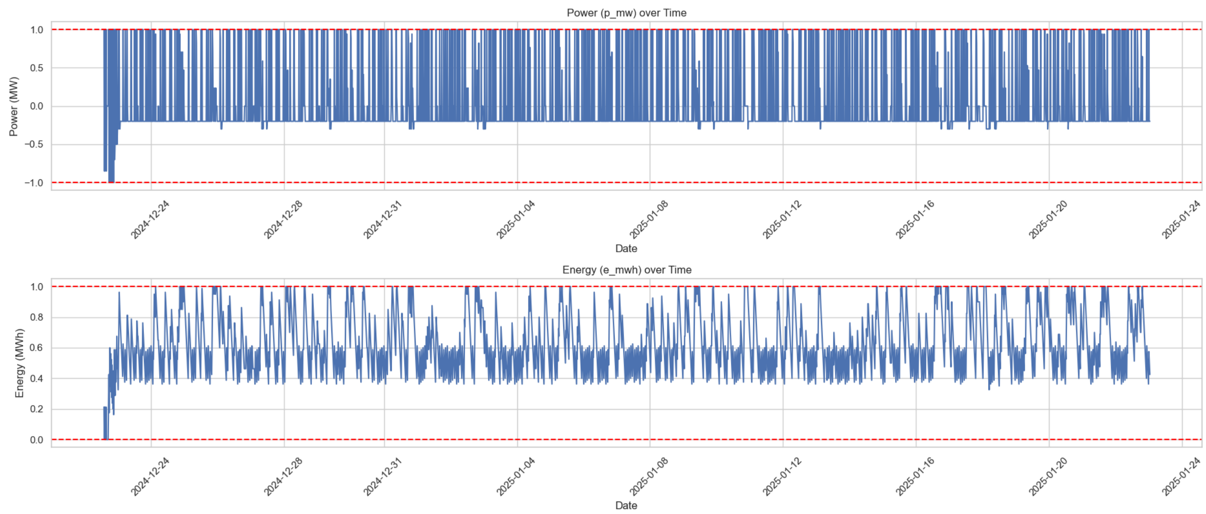
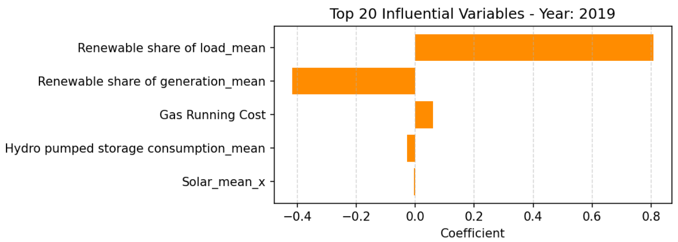


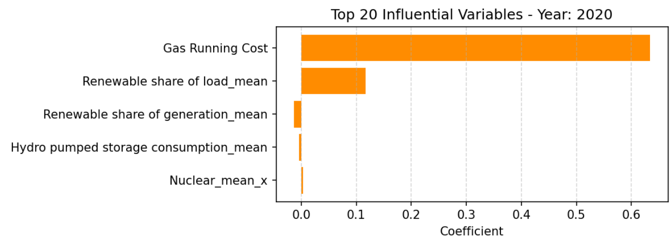
Figure 40: Power and Energy in the Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day for 2h Battery

C Day-Ahead Market Analysis

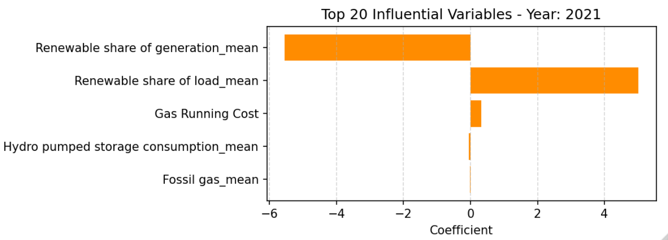
C.1 Linear Regression



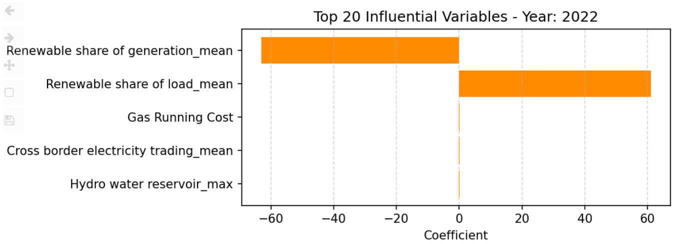
(a) 2019



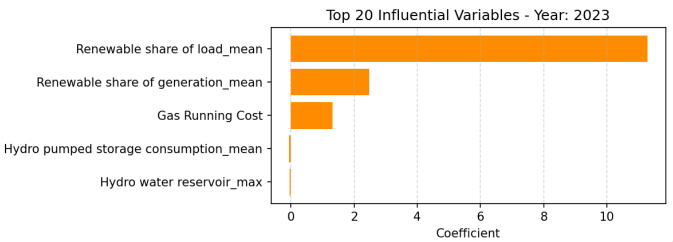
(b) 2020



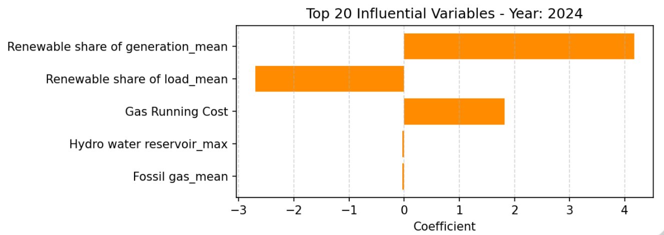
(c) 2021



(d) 2022



(e) 2023

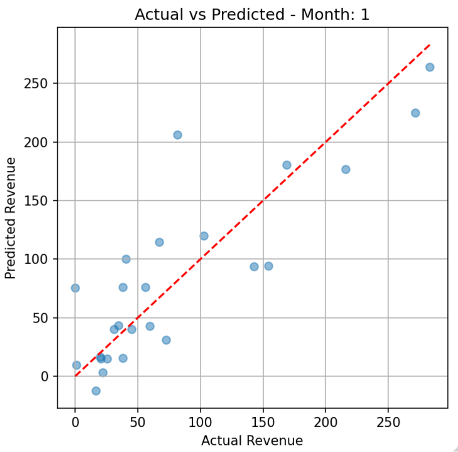


(f) 2024

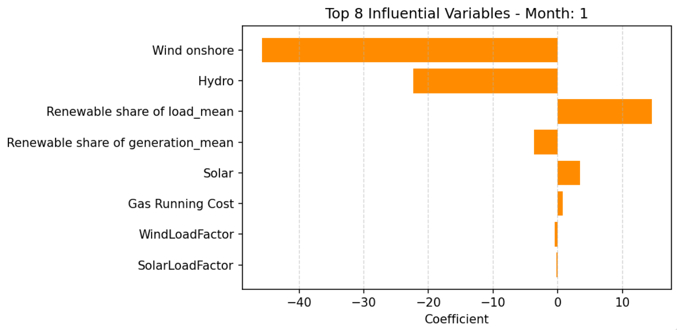
Figure 41: Annual linear regression coefficients for battery revenue prediction (2019–2024). The plots show the most relevant market and technical drivers per year.

Table 17: Regression model performance by year (test set).

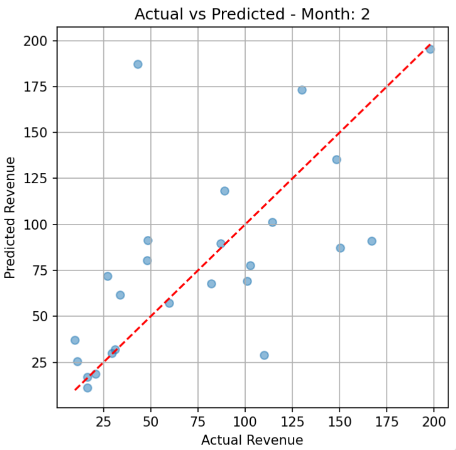
Year	R^2	MSE
2019	0.655	118.46(€^{2})
2020	0.788	45.81(€^{2})
2021	0.602	1825.33 (€^{2})
2022	0.283	7705.51 (€^{2})
2023	0.327	2983.11 (€^{2})
2024	0.502	3424.33 (€^{2})



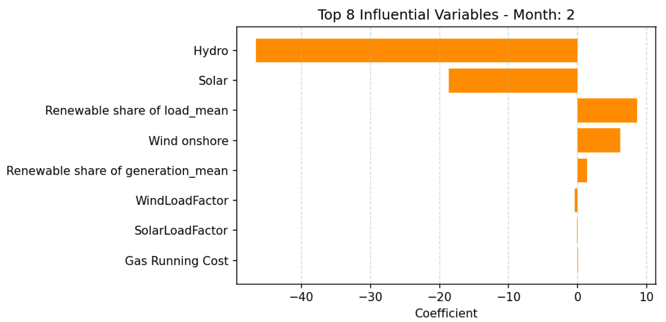
Month 1 – Scatter
R^2: 0.722, MSE: 1735.71(€^{2})



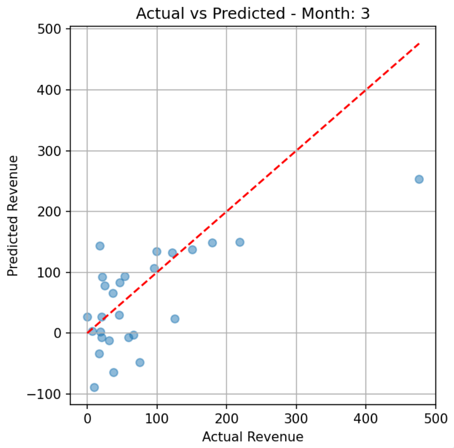
Month 1 – Coefficients



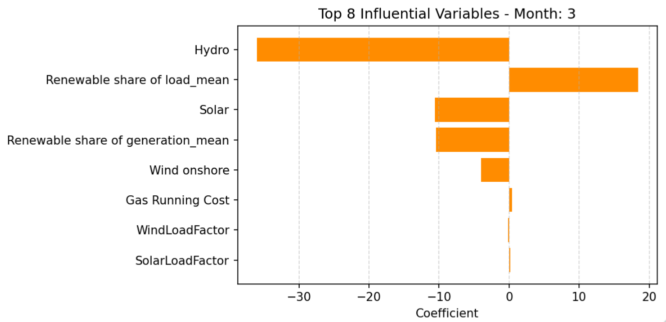
Month 2 – Scatter
R^2: 0.315, MSE: 1944.81(€^{2})



Month 2 – Coefficients

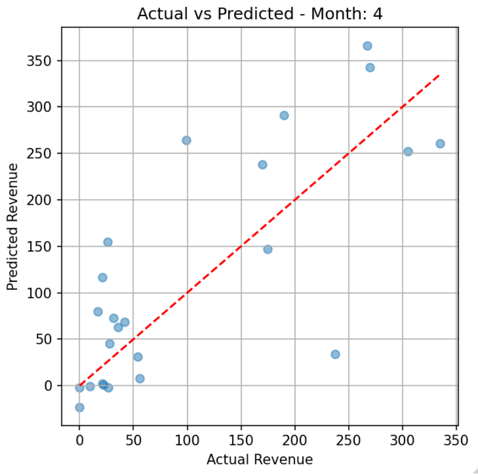


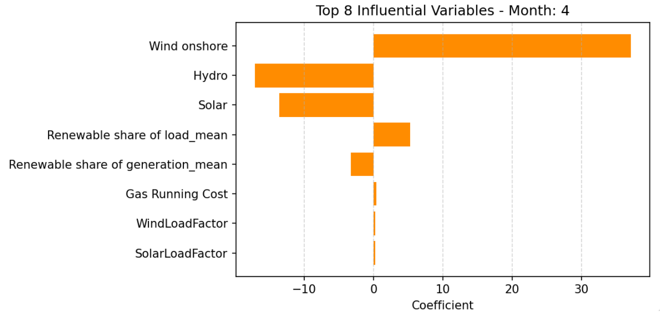
Month 3 – Scatter
R^2: 0.409, MSE: 5402.84(€^{2})



Month 3 – Coefficients

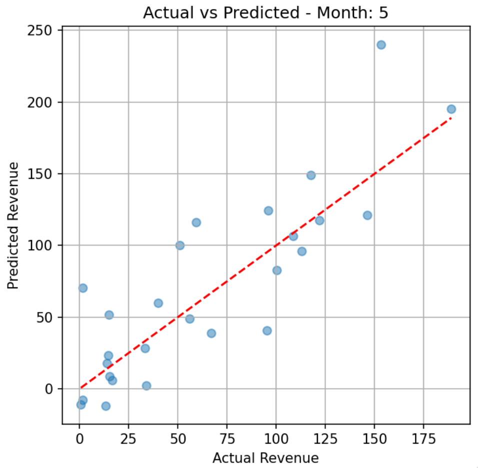
Figure 42: Monthly regression results (January to March).

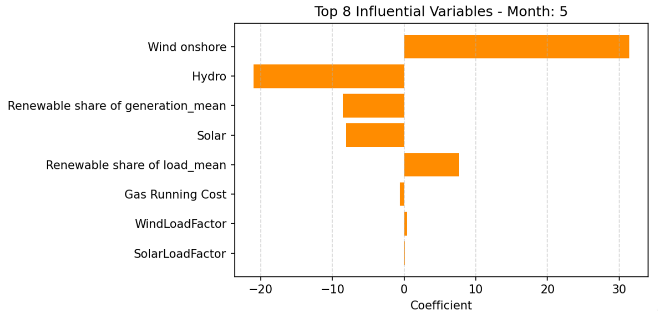




Month 4 – Coefficients

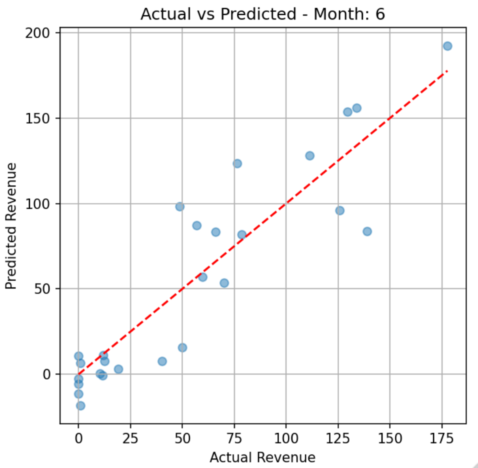
Month 4 – Scatter
R^2: 0.474, MSE: 6081.03(€^{2})

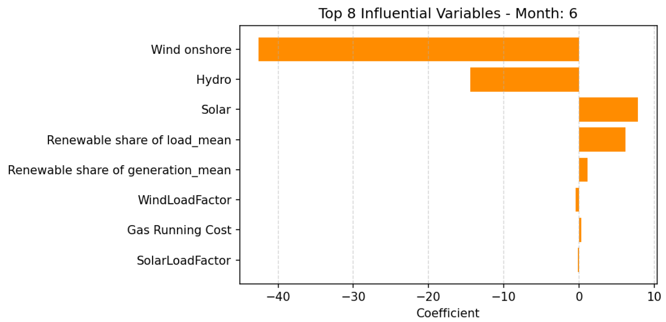




Month 5 – Coefficients

Month 5 – Scatter
R^2: 0.606, MSE: 1108.57(€^{2})

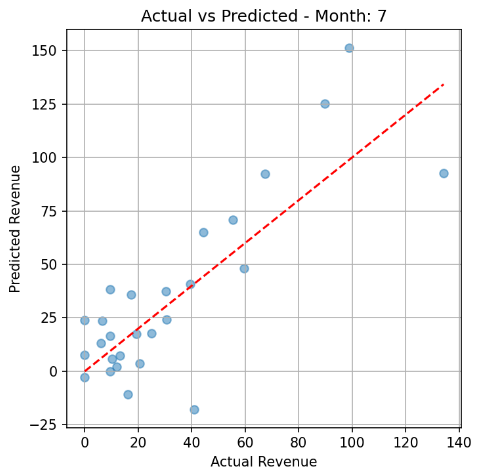




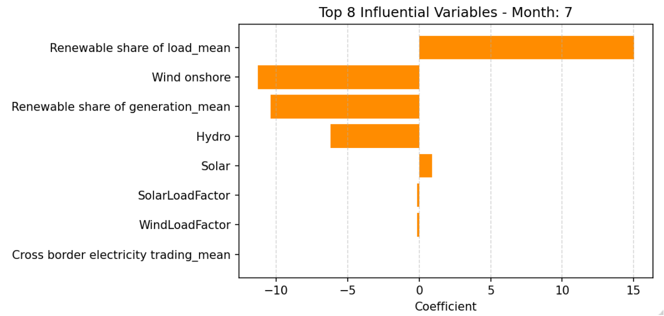
Month 6 – Coefficients

Month 6 – Scatter
R^2: 0.786, MSE: 579.56(€^{2})

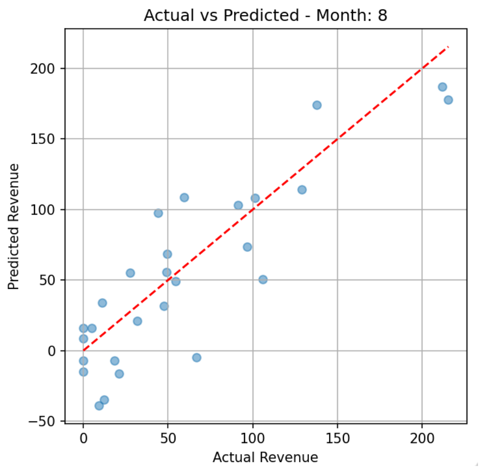
Figure 43: Monthly regression results (April to June).



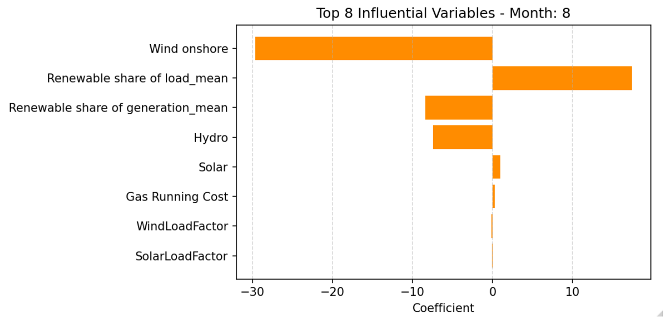
Month 7 – Scatter
R^2: 0.510, MSE: 526.80(€^{2})



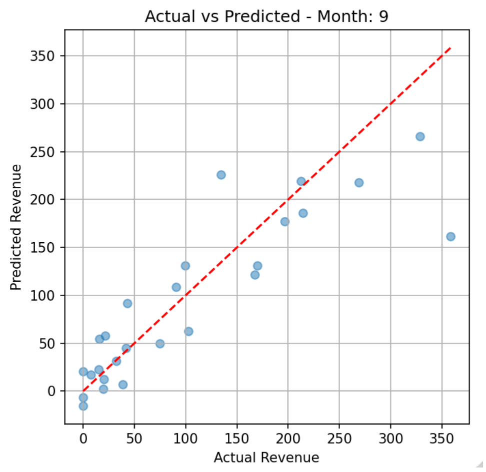
Month 7 – Coefficients



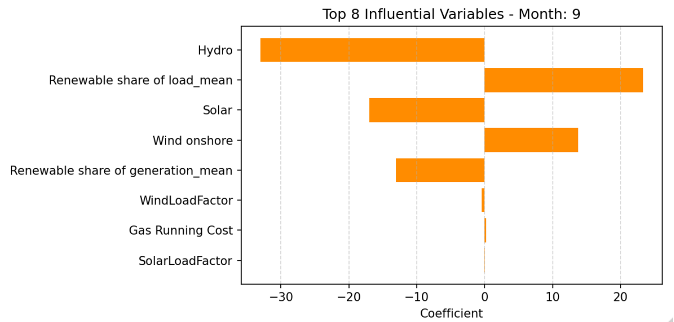
Month 8 – Scatter
R^2: 0.713, MSE: 1003.89(€^{2})



Month 8 – Coefficients

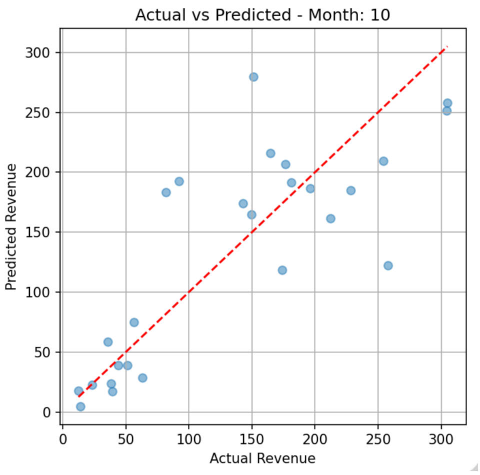


Month 9 – Scatter
R^2: 0.752, MSE: 2678.83(€^{2})

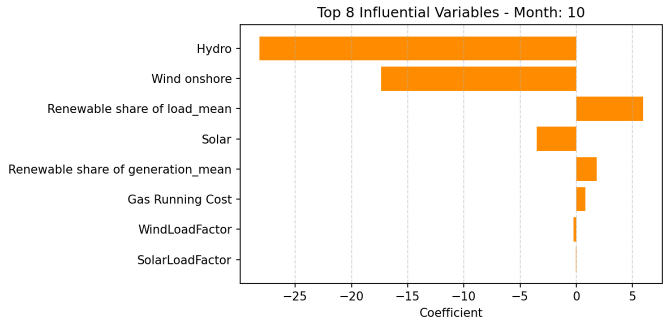


Month 9 – Coefficients

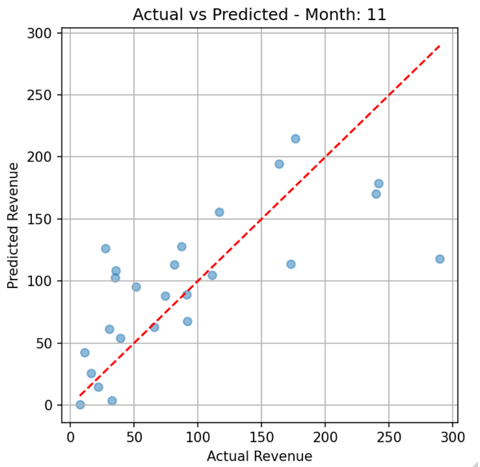
Figure 44: Monthly regression results (July to September).



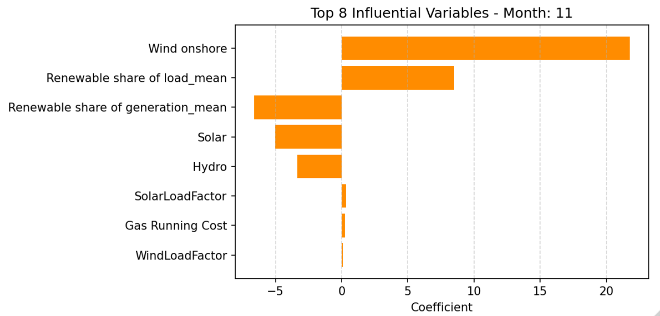
Month 10 – Scatter
R^2: 0.636, MSE: 2990.58(€^{2})



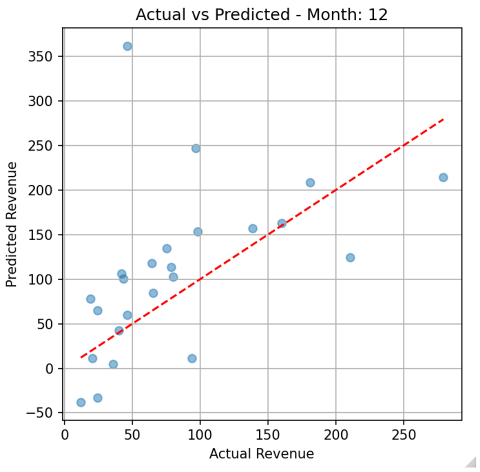
Month 10 – Coefficients



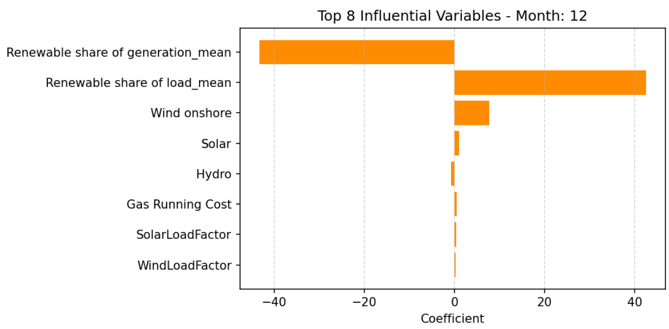
Month 11 – Scatter
R^2: 0.510, MSE: 2955.47(€^{2})



Month 11 – Coefficients



Month 12 – Scatter
R^2: 0.651, MSE: 7206.29(€^{2})



Month 12 – Coefficients

Figure 45: Monthly regression results (October to December).

Table 18: Summary of monthly regression model performance (2019–2025).

Month	R^2	**MSE(€^{2})**
January	0.722	1735.71
February	0.315	1944.81
March	0.409	5402.84
April	0.474	6081.03
May	0.606	1108.57
June	0.786	579.56
July	0.510	526.80
August	0.713	1003.89
September	0.752	2678.83
October	0.636	2990.58
November	0.510	2955.47
December	-0.651	7206.29

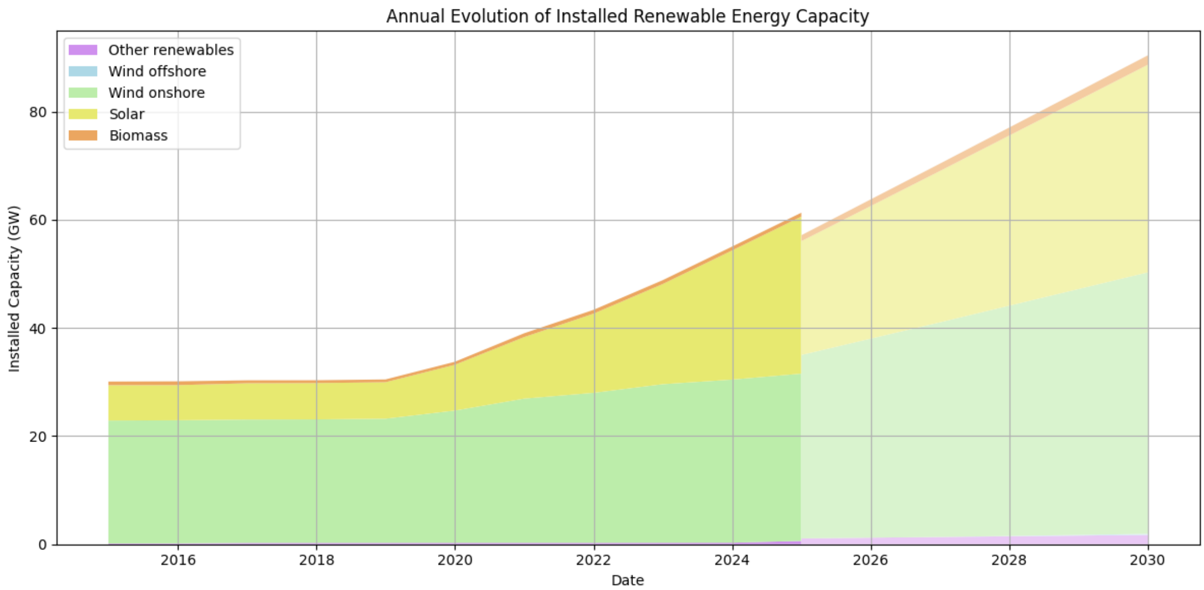


Figure 46: Installed Capacity of Renewable Energy Technology in Spain and expected growth forecasted in the 2023 Yearly Adequacy Report by REE (TSO) [53]

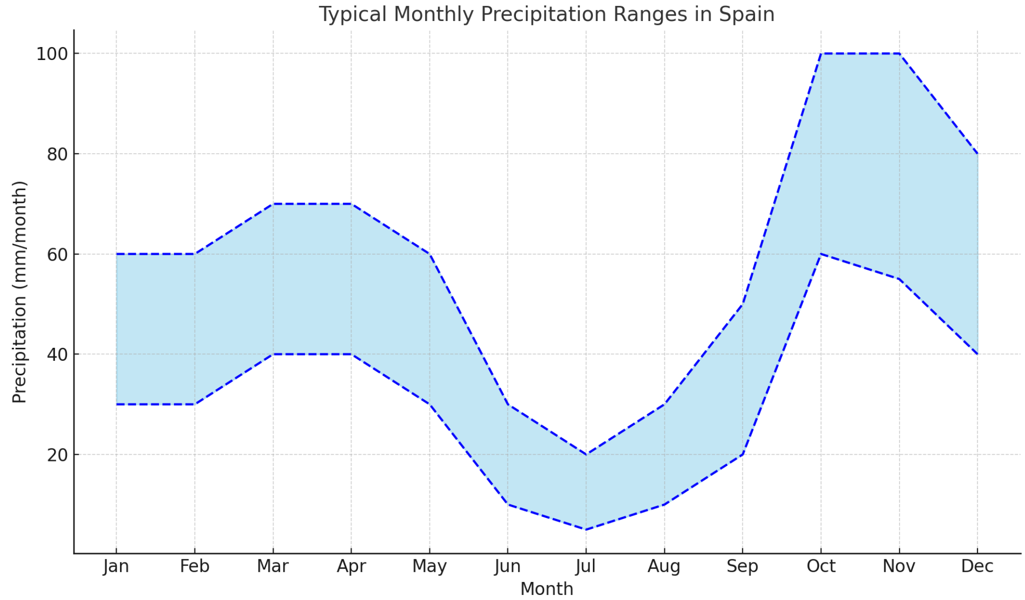


Figure 47: Typical monthly precipitation ranges in Spain (in mm/month). Autumn and early winter months (October–December) show the highest rainfall levels, with values often exceeding 100 mm. Data based on AEMET and historical climate averages from 1991–2020.

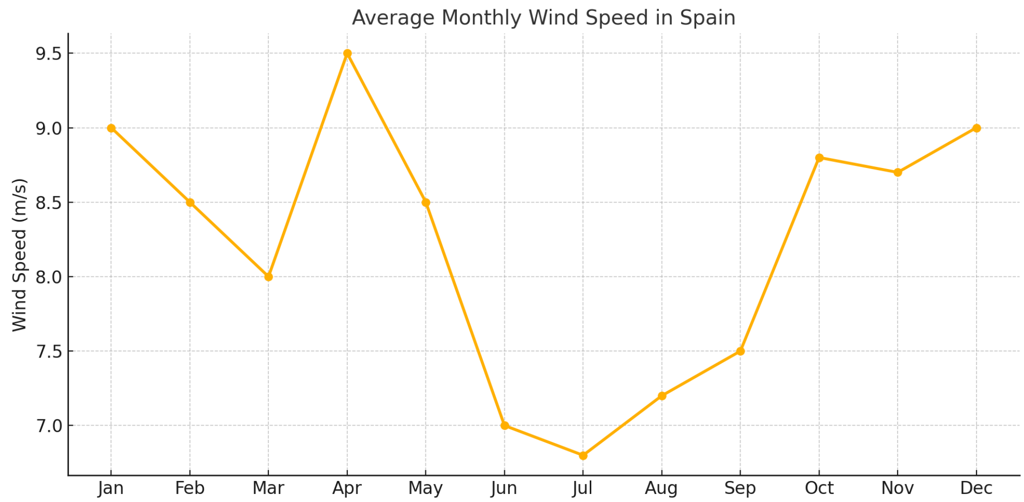


Figure 48: Average monthly wind speed in Spain.

C.2 Gas Running Cost

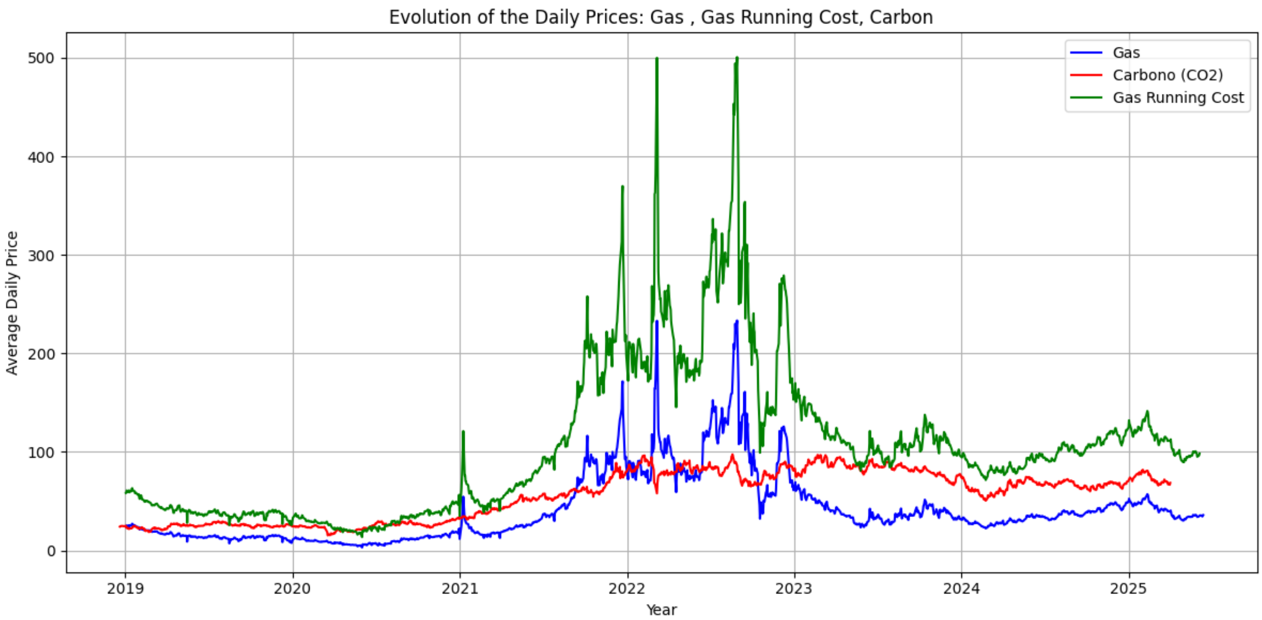


Figure 49: Gas Price, CO2 Price and Gas Running Cost

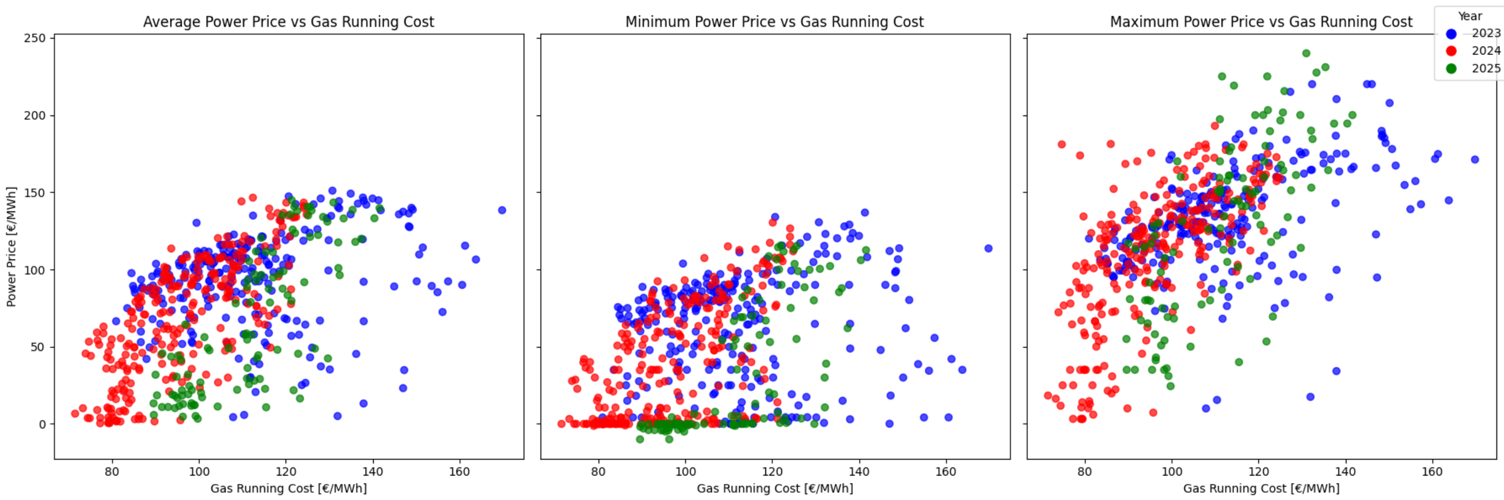


Figure 50: Correlation between gas running cost and maximum, minimum, and average power prices.

Table 19: Correlation between Weekly Gas Running Cost and Battery Revenue (2019–2025)

Year	Gas Metric	Pearson Correlation	Slope	R^2
2019	Average	0.0331	0.3725	0.0011
2019	Minimum	-0.0031	-0.0339	0.0000
2019	Maximum	0.1365	1.6152	0.0186
2020	Average	0.7371	6.1898	0.5433
2020	Minimum	0.6911	5.8829	0.4777
2020	Maximum	0.7607	6.0987	0.5786
2021	Average	0.5912	2.8600	0.3495
2021	Minimum	0.5632	2.8040	0.3172
2021	Maximum	0.6008	2.8334	0.3609
2022	Average	0.0298	0.2042	0.0009
2022	Minimum	-0.0044	-0.0301	0.0000
2022	Maximum	0.0896	0.6308	0.0080
2023	Average	0.3248	5.6090	0.1055
2023	Minimum	0.3363	6.0907	0.1131
2023	Maximum	0.3095	4.9936	0.0958
2024	Average	0.3049	8.2224	0.0929
2024	Minimum	0.3089	8.3538	0.0954
2024	Maximum	0.2994	8.0055	0.0896
2025	Average	0.3427	11.5566	0.1174
2025	Minimum	0.3468	11.8908	0.1203
2025	Maximum	0.3390	11.3332	0.1149

C.3 Power Prices

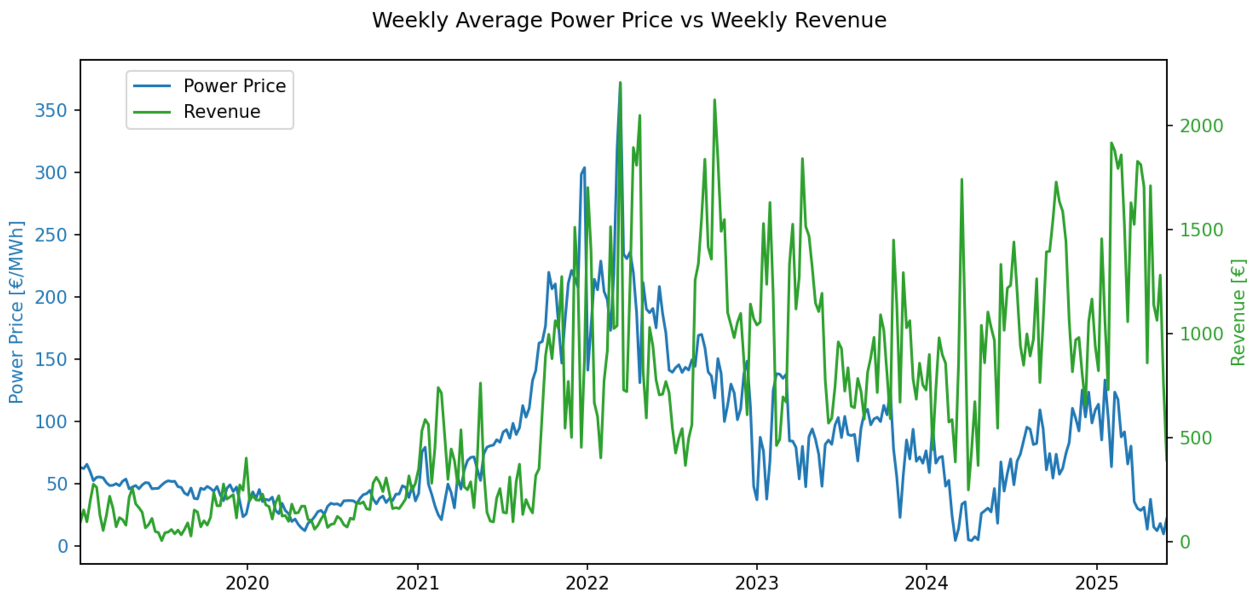


Figure 51: Correlation between the Weekly Average Power Price and the Battery Revenue

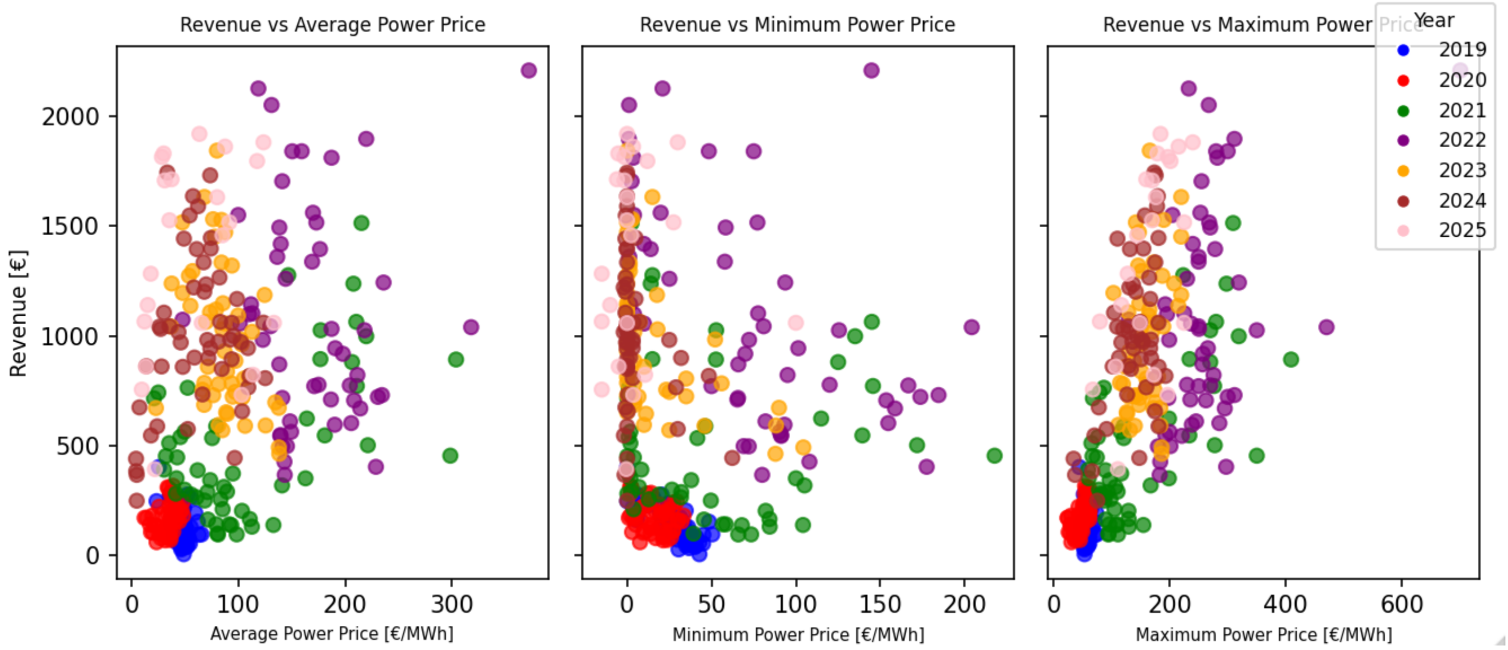


Figure 52: Correlation between the Power Prices and Revenue

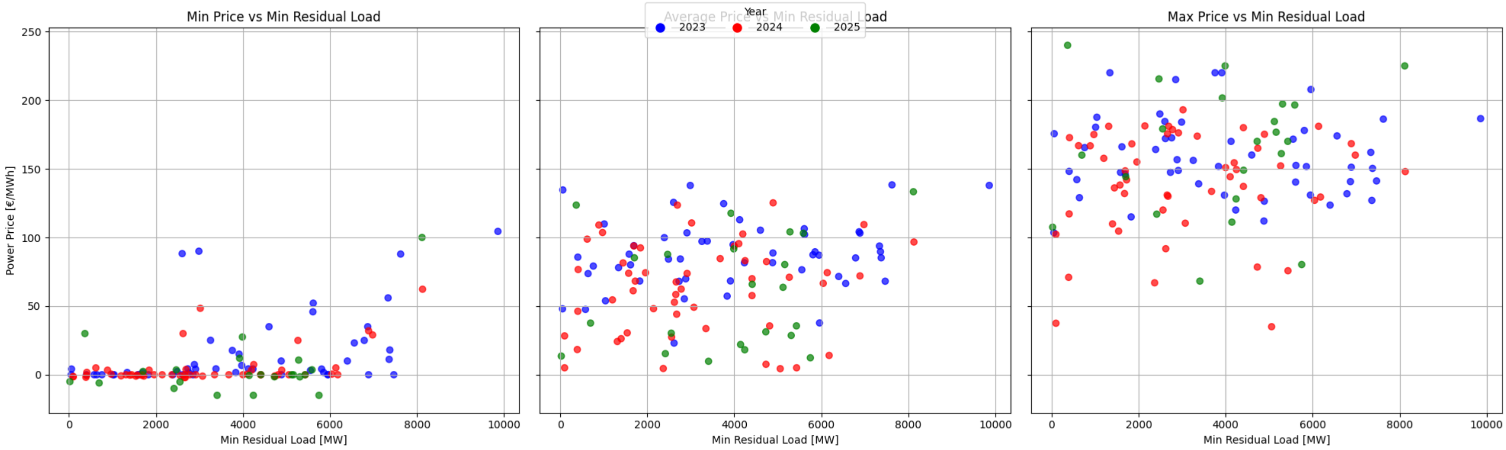


Figure 53: Correlation Between the Power Prices and the Minimum Residual Load

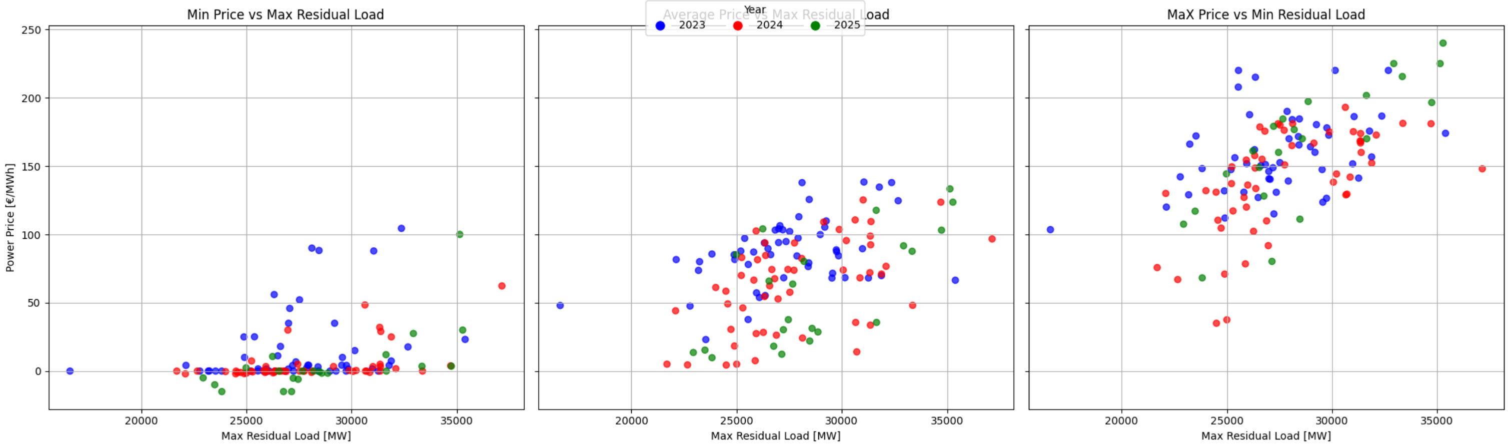


Figure 54: Correlation Between the Power Prices and the Maximum Residual Load

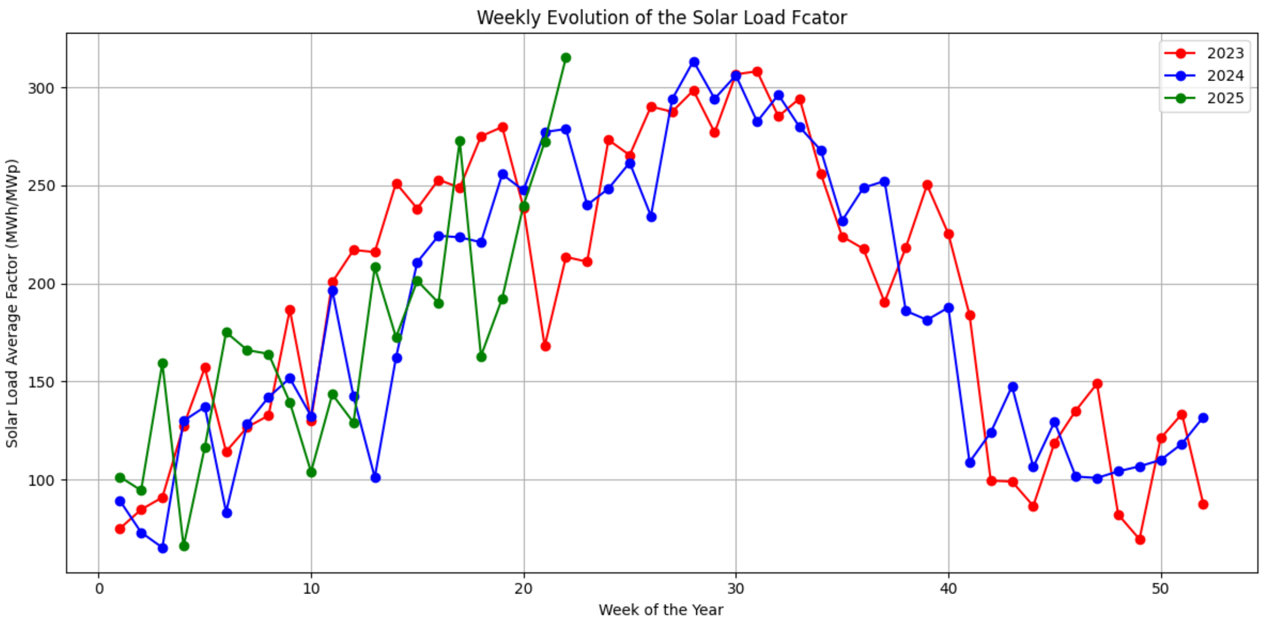


Figure 55: Evolution of the weekly Solar Factor in Spain from 2023

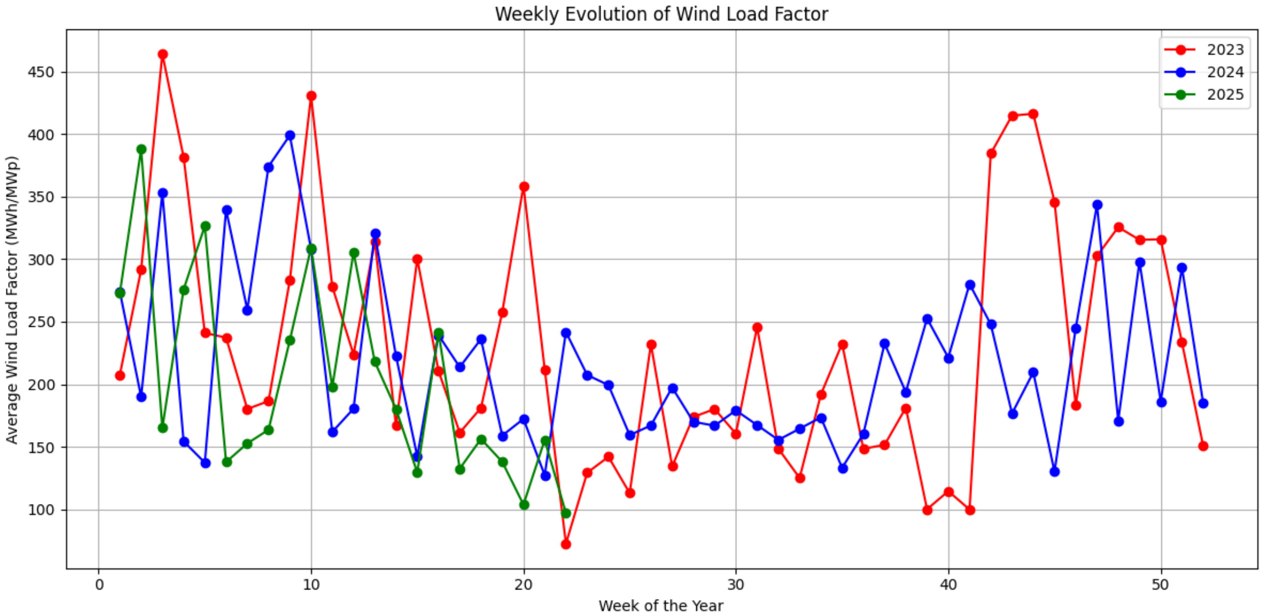


Figure 56: Evolution of the Weekly Wind Factor in Spain from 2023

Table 20: Regression results: Power prices vs. Battery revenue (2020–2022)

Metric	**2020**			**2021**			**2022**		
	Corr.	Slope	R^2	Corr.	Slope	R^2	Corr.	Slope	R^2
Average	0.3365	2.64	0.1132	0.5172	2.49	0.2675	0.0322	0.29	0.0010
Minimum	-0.2679	-1.91	0.0717	0.0106	0.07	0.0001	-0.4992	-4.27	0.2492
Maximum	0.6098	3.70	0.3719	0.6613	2.52	0.4374	0.3868	2.32	0.1496

Table 21: Regression results: Power prices vs. Battery revenue (2023–2025)

Metric	**2023**			**2024**			**2025**		
	Corr.	Slope	R^2	Corr.	Slope	R^2	Corr.	Slope	R^2
Average	-0.4077	-5.17	0.1662	0.2320	2.45	0.0538	0.1865	2.05	0.0348
Minimum	-0.4846	-6.01	0.2348	-0.2692	-7.26	0.0725	0.0157	0.30	0.0002
Maximum	0.3234	3.70	0.1046	0.5493	5.10	0.3017	0.5839	5.66	0.3409

C.4 Residual Load

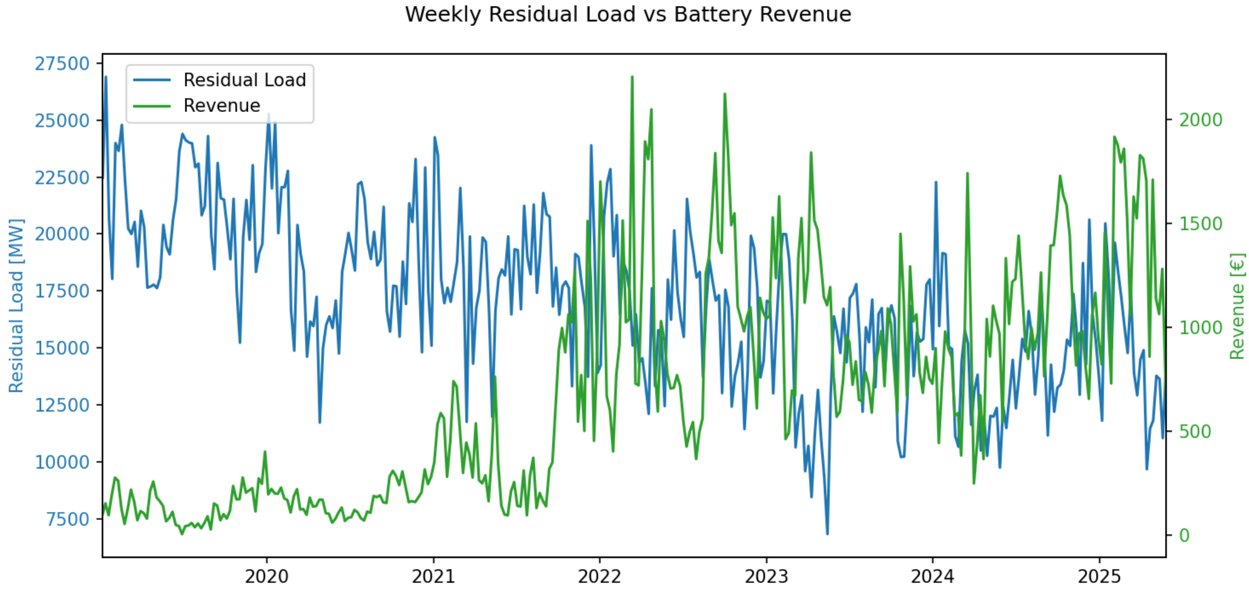


Figure 57: Battery Revenue compared to Weekly Residual Load

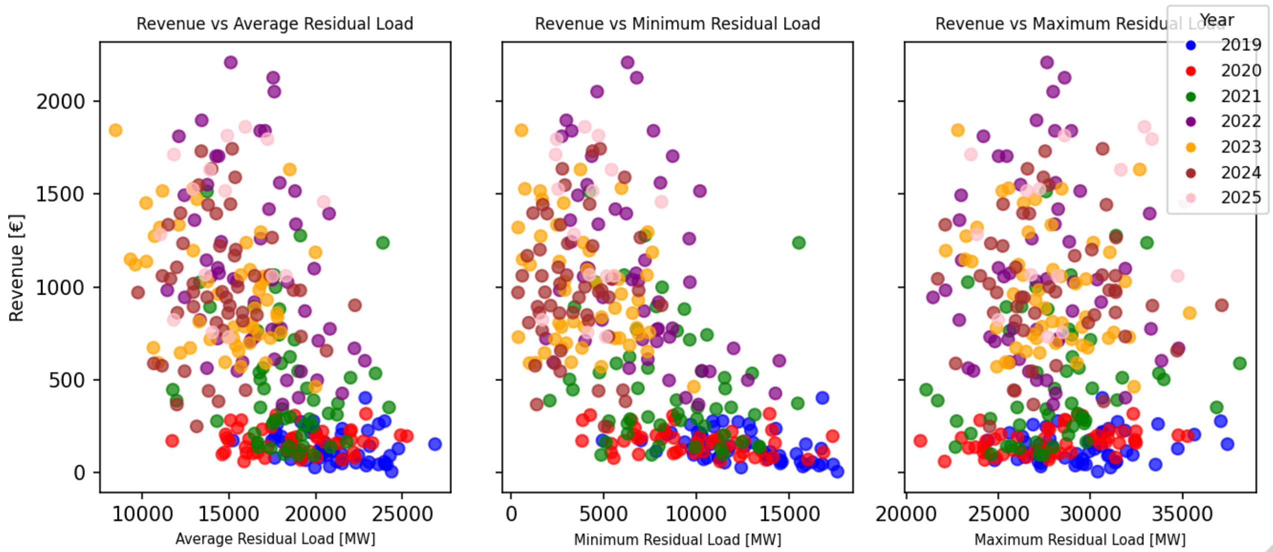


Figure 58: Correlation between the Battery Revenue and the Residual Load

Table 22: Regression results: Residual Load vs. Battery revenue (2020–2022)

Metric	**2020**			**2021**			**2022**		
	Corr.	Slope	R^2	Corr.	Slope	R^2	Corr.	Slope	R^2
Average	0.0297	0.0007	0.0009	-0.1922	-0.0246	0.0369	-0.3277	-0.0581	0.1074
Minimum	-0.3391	-0.0068	0.1150	-0.2027	-0.0212	0.0411	-0.4360	-0.0708	0.1901
Maximum	0.3461	0.0070	0.1198	0.1777	0.0176	0.0316	-0.0447	-0.0072	0.0020

Table 23: Regression results: Residual Load vs. Battery revenue (2023–2025)

Metric	**2023**			**2024**			**2025**		
	Corr.	Slope	R^2	Corr.	Slope	R^2	Corr.	Slope	R^2
Average	-0.3777	-0.0429	0.1426	-0.0175	-0.0024	0.0003	0.0923	0.0140	0.0085
Minimum	-0.2914	-0.0401	0.0849	-0.0332	-0.0064	0.0011	-0.0696	-0.0171	0.0048
Maximum	-0.2697	-0.0311	0.0728	-0.0138	-0.0015	0.0002	0.2468	0.0259	0.0609

C.5 Load

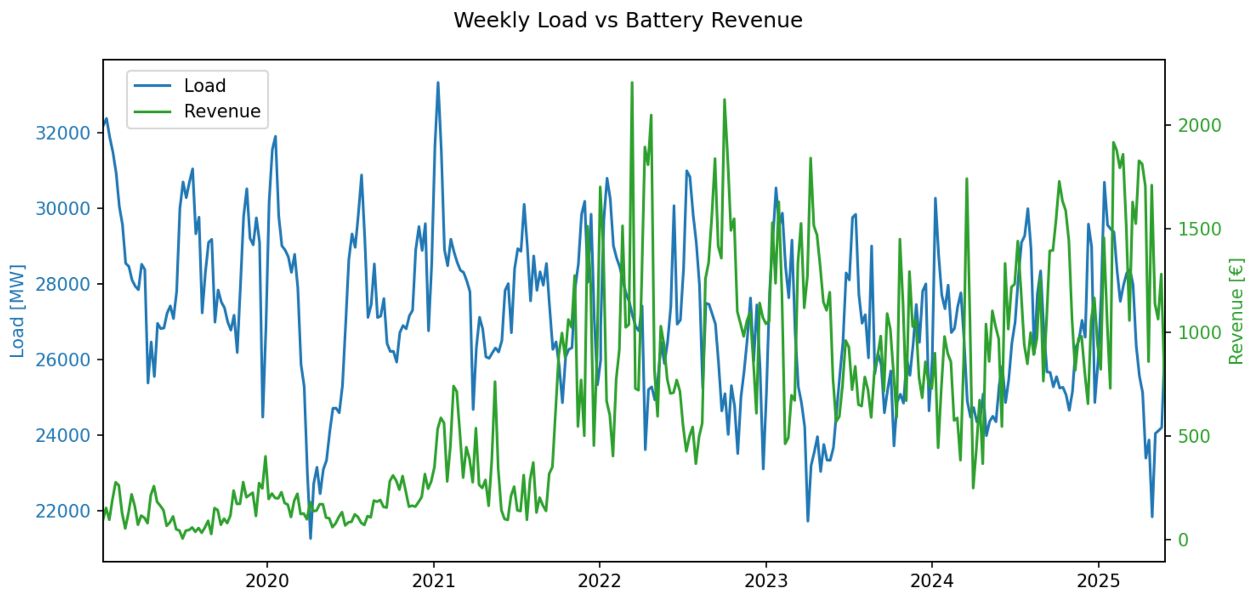


Figure 59: Battery Revenue compared to Weekly Load

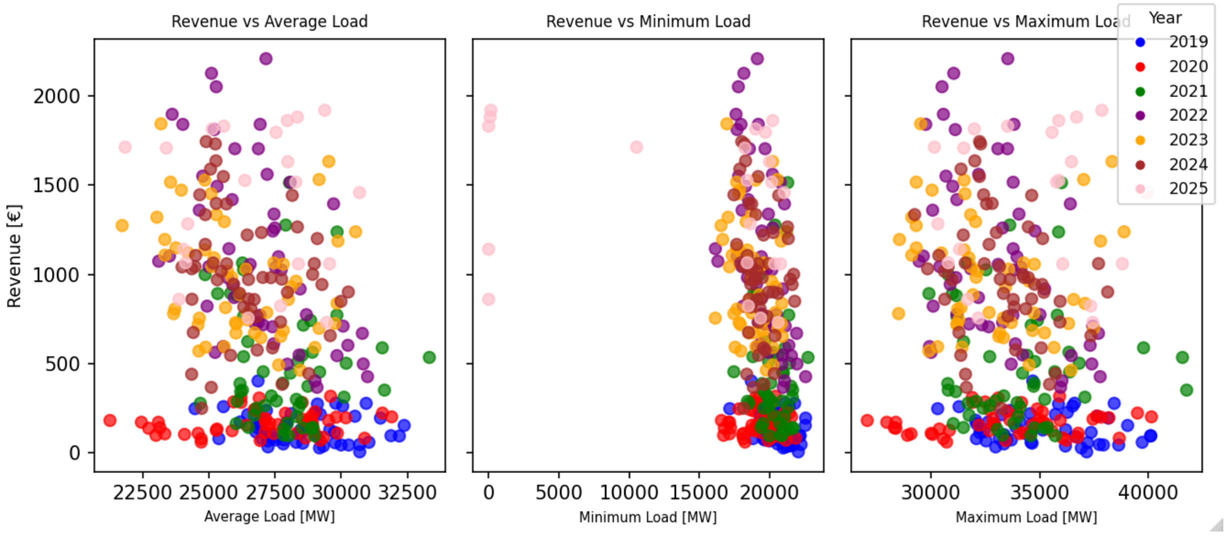


Figure 60: Correlation between the Battery Revenue and Load

Table 24: Regression results: Load vs. battery revenue (2020–2022)

Metric	**2020**			**2021**			**2022**		
	Corr.	Slope	R^2	Corr.	Slope	R^2	Corr.	Slope	R^2
Average	0.1733	0.0047	0.0300	-0.0815	-0.0160	0.0066	-0.5009	-0.1275	0.2509
Minimum	0.0663	0.0032	0.0044	-0.1389	-0.0448	0.0193	-0.5538	-0.1927	0.3067
Maximum	0.1429	0.0031	0.0204	-0.0395	-0.0052	0.0016	-0.4084	-0.0849	0.1668

Table 25: Regression results: Load vs. battery revenue (2023–2025)

Metric	**2023**			**2024**			**2025**		
	Corr.	Slope	R^2	Corr.	Slope	R^2	Corr.	Slope	R^2
Average	-0.2611	-0.0401	0.0682	-0.1929	-0.0400	0.0372	-0.0185	-0.0031	0.0003
Minimum	-0.2427	-0.0600	0.0589	-0.1778	-0.0565	0.0316	-0.2153	-0.0104	0.0463
Maximum	-0.1791	-0.0214	0.0321	-0.2708	-0.0476	0.0733	0.0470	0.0064	0.0022

D Codes

D.1 aFRR Trading Strategies Codes

D.1.1 Deterministic benchmark (energy only)

```
import numpy as np
from dataclasses import dataclass

@dataclass
class Battery:
    p_min_mw: float
    p_max_mw: float
    e_min_mwh: float
    e_max_mwh: float
    eff_charge: float
    eff_discharge: float
    max_cycles_per_day: float

battery = Battery(
    p_min_mw=1.0,
    p_max_mw=1.0,
    e_min_mwh=0.0,
    e_max_mwh=4.0,
    eff_charge=0.85,
    eff_discharge=1.0,
    max_cycles_per_day=2.0
)

T = len(up_marginal_price_vector)

energy_step = 0.05
energy_levels = np.round(np.arange(
    battery.e_min_mwh,
    battery.e_max_mwh + energy_step,
    energy_step
), 5)
n_levels = len(energy_levels)

V = np.zeros((T + 1, n_levels))
policy = np.zeros((T, n_levels))

actions = np.round(np.arange(
    -battery.p_max_mw,
    battery.p_max_mw + energy_step,
    energy_step
), 5)

for t in reversed(range(T)):
    up_price = up_marginal_price_vector[t]
    down_price = dn_marginal_price_vector[t]
    for idx, energy in enumerate(energy_levels):
        best_value = -np.inf
        best_action = 0.0
        for action in actions:
            if action > 0:
                post_energy = energy + (action * battery.eff_charge) * 0.25
```

```
                immediate_revenue = -action * down_price * 0.25
            elif action < 0:
                post_energy = energy + (action / battery.eff_discharge) * 0.25
                immediate_revenue = -action * up_price * 0.25
            else:
                post_energy = energy
                immediate_revenue = 0.0

            if battery.e_min_mwh <= post_energy <= battery.e_max_mwh:
                new_idx = int(round((post_energy - battery.e_min_mwh) / energy_step))
                future_value = V[t + 1, new_idx]
                total_value = immediate_revenue + future_value
                if total_value > best_value:
                    best_value = total_value
                    best_action = action

        V[t, idx] = best_value
        policy[t, idx] = best_action

current_energy = battery.e_max_mwh * 0.5
soc_history = [current_energy]
action_history = []
revenue_history = []
cycles_history = []
rolling_cycles_history = []

for t in range(T):
    idx = int(round((current_energy - battery.e_min_mwh) / energy_step))
    action = policy[t, idx]
    up_price = up_marginal_price_vector[t]
    down_price = dn_marginal_price_vector[t]

    if action > 0:
        energy_delta = (action * battery.eff_charge) * 0.25
        immediate_revenue = -action * down_price * 0.25
    elif action < 0:
        energy_delta = (action / battery.eff_discharge) * 0.25
        immediate_revenue = -action * up_price * 0.25
    else:
        energy_delta = 0.0
        immediate_revenue = 0.0

    current_energy = np.clip(
        current_energy + energy_delta,
        battery.e_min_mwh,
        battery.e_max_mwh
    )
    soc_history.append(current_energy)
    action_history.append(action)
    revenue_history.append(immediate_revenue)

    cycle_contrib = (
        -action * 0.25
    ) / (battery.e_max_mwh * battery.eff_discharge) if action < 0 else 0.0
    cycles_history.append(cycle_contrib)
    if t < 96:
        rolling_cycles = sum(cycles_history)
```

```
    else:
        rolling_cycles = sum(cycles_history[t-95:t+1])
    rolling_cycles_history.append(rolling_cycles)

total_revenue = sum(revenue_history)
```

D.1.2 Deterministic benchmark (energy + capacity)

```
import numpy as np
from dataclasses import dataclass

@dataclass
class Battery:
    p_min_mw: float
    p_max_mw: float
    e_min_mwh: float
    e_max_mwh: float
    eff_charge: float
    eff_discharge: float
    max_cycles_per_day: float

@dataclass
class CapacityMarket:
    cap_min_mw: float
    cap_max_mw: float
    step: float

battery_2h = Battery(
    p_min_mw=1.0,
    p_max_mw=1.0,
    e_min_mwh=0.0,
    e_max_mwh=4.0,
    eff_charge=0.85,
    eff_discharge=1.0,
    max_cycles_per_day=2.0
)

capacity_2h = CapacityMarket(
    cap_min_mw=0.0,
    cap_max_mw=1.0,
    step=0.05
)

n_steps = 2880
energy_step = 0.05
energy_levels = np.round(
    np.arange(battery_2h.e_min_mwh, battery_2h.e_max_mwh + energy_step, energy_step),
    5
)
n_levels = len(energy_levels)
reserved_capacity_levels = np.round(
    np.arange(capacity_2h.cap_min_mw, capacity_2h.cap_max_mw + capacity_2h.step,
         capacity_2h.step),
    5
)

```

```
# DP tables\ nV = np.zeros((n_steps + 1, n_levels))
policy_reserved = np.zeros((n_steps, n_levels))
policy_power = np.zeros((n_steps, n_levels))

power_actions = np.round(
    np.arange(-battery_2h.p_max_mw, battery_2h.p_max_mw + energy_step, energy_step),
    5
)

for t in reversed(range(n_steps)):
    up_price = up_marginal_price_vector[t]
    down_price = dn_marginal_price_vector[t]
    capacity_price = up_marginal_capacity_price[t]
    imbalance_price = up_marginal_imbalance_price[t]

    for idx, energy in enumerate(energy_levels):
        best_value = -np.inf
        best_reserved = 0.0
        best_action = 0.0

        for reserved in reserved_capacity_levels:
            min_energy = reserved
            if energy < min_energy:
                needed_energy = min_energy - energy
                imbalance_cost = needed_energy * imbalance_price
            else:
                needed_energy = 0.0
                imbalance_cost = 0.0

            capacity_rev = reserved * capacity_price * 0.25

            for action in power_actions:
                if action > 0:
                    delta = action * battery_2h.eff_charge * 0.25
                    energy_rev = -action * down_price * 0.25
                elif action < 0:
                    delta = action / battery_2h.eff_discharge * 0.25
                    energy_rev = -action * up_price * 0.25
                else:
                    delta = 0.0
                    energy_rev = 0.0

                post_energy = energy + delta + needed_energy
                if battery_2h.e_min_mwh <= post_energy <= battery_2h.e_max_mwh:
                    new_idx = int(round((post_energy - battery_2h.e_min_mwh) / energy_step))
                    future_value = V[t + 1, new_idx]
                    total = capacity_rev + energy_rev - imbalance_cost + future_value

                    if total > best_value:
                        best_value = total
                        best_reserved = reserved
                        best_action = action

        V[t, idx] = best_value
        policy_reserved[t, idx] = best_reserved
        policy_power[t, idx] = best_action

```

```
# Simulation using optimal policy
current_energy = battery_2h.e_max_mwh * 0.5
soc_history = [current_energy]
power_history = []
reserved_history = []
revenue_history = []
capacity_rev_history = []
imbalance_cost_history = []
cycles_history = []
rolling_cycles_history = []

for t in range(n_steps):
    idx = int(round((current_energy - battery_2h.e_min_mwh) / energy_step))
    reserved = policy_reserved[t, idx]
    action = policy_power[t, idx]

    up_price = up_marginal_price_vector[t]
    down_price = dn_marginal_price_vector[t]
    cap_price = up_marginal_capacity_price[t]
    imb_price = up_marginal_imbalance_price[t]

    if current_energy < reserved:
        needed_energy = reserved - current_energy
        imb_cost = needed_energy * imb_price
    else:
        needed_energy = 0.0
        imb_cost = 0.0

    cap_rev = reserved * cap_price * 0.25

    if action > 0:
        delta = action * battery_2h.eff_charge * 0.25
        energy_rev = -action * down_price * 0.25
    elif action < 0:
        delta = action / battery_2h.eff_discharge * 0.25
        energy_rev = -action * up_price * 0.25
    else:
        delta = 0.0
        energy_rev = 0.0

    total_rev = cap_rev + energy_rev - imb_cost

    current_energy = np.clip(
        current_energy + delta + needed_energy,
        battery_2h.e_min_mwh,
        battery_2h.e_max_mwh
    )

    soc_history.append(current_energy)
    reserved_history.append(reserved)
    power_history.append(action)
    revenue_history.append(total_rev)
    capacity_rev_history.append(cap_rev)
    imbalance_cost_history.append(imb_cost)

    cycle_contrib = (-action * 0.25) / (battery_2h.e_max_mwh * battery_2h.eff_discharge) if
        action < 0 else 0.0
```

```
        cycles_history.append(cycle_contrib)

        if t < 96:
            rolling = sum(cycles_history)
        else:
            rolling = sum(cycles_history[t-95:t+1])

        rolling_cycles_history.append(rolling)

    total_revenue = sum(revenue_history)
    print(f"Total revenue: {total_revenue:.2f} ")
```

D.1.3 Heuristic: Energy-only participation

```
from dataclasses import dataclass
import numpy as np

@dataclass
class Battery:
    p_min_mw: float
    p_max_mw: float
    e_min_mwh: float
    e_max_mwh: float
    eff_charge: float
    eff_discharge: float
    max_cycles_per_day: float

battery_2h = Battery(
    p_min_mw=1.0,
    p_max_mw=1.0,
    e_min_mwh=0.0,
    e_max_mwh=2.0,
    eff_charge=0.85,
    eff_discharge=1.0,
    max_cycles_per_day=2.0
)

n_qhs = len(dn_marginal_price_vector)
n_up_premiums = int(up_percentiles[3] - up_percentiles[1])
n_down_premiums = n_up_premiums

up_premiums = np.arange(n_up_premiums)
dn_premiums = np.arange(n_down_premiums)

final_revenue = np.zeros((n_up_premiums, n_down_premiums))
mean_cycles_day = np.zeros((n_up_premiums, n_down_premiums))

for i_up, up_p in enumerate(up_premiums):
    for j_dn, dn_p in enumerate(dn_premiums):
        e_current = battery_2h.e_max_mwh * 0.5
        e_history = np.zeros(n_qhs)
        revenue = np.zeros(n_qhs)
        revenue_accum = np.zeros(n_qhs)
        cycles_per_day = np.zeros(n_qhs)
        verify_cycles = np.zeros(n_qhs)

```

```
        for t in range(n_qhs):
            if t < 8:
                up_price = np.min(up_marginal_price[:t+1]) + up_p
                dn_price = np.max(dn_marginal_price[:t+1]) - dn_p
            else:
                up_price = np.min(up_marginal_price[t-8:t]) + up_p
                dn_price = np.max(dn_marginal_price[t-8:t]) - dn_p

            up_volume = 0 if t == 0 else min(
                battery_2h.p_max_mw,
                e_history[t-1] * 4 * battery_2h.eff_discharge
            )
            dn_volume = (battery_2h.p_max_mw if t == 0 else min(
                battery_2h.p_max_mw,
                (battery_2h.e_max_mwh - e_history[t-1]) * 4 / battery_2h.eff_charge
            ))

            p_up = up_volume if up_price <= up_marginal_price[t] else 0
            p_dn = dn_volume if dn_price >= dn_marginal_price[t] else 0

            if p_up > 0:
                p_dn = 0
            elif p_dn > 0:
                p_up = 0

            p_set = p_dn - p_up
            e_current = np.clip(
                e_current + (max(p_set, 0) * battery_2h.eff_charge + min(p_set, 0) /
                    battery_2h.eff_discharge) * 0.25,
                battery_2h.e_min_mwh,
                battery_2h.e_max_mwh
            )
            e_history[t] = e_current

            if p_set < 0:
                cycles_per_day[t] = -p_set * 0.25 / (battery_2h.e_max_mwh *
                    battery_2h.eff_discharge)
            verify_cycles[t] = np.sum(cycles_per_day[max(0, t-95):t+1])

            revenue[t] = (p_up * up_marginal_price[t] - p_dn * dn_marginal_price[t]) * 0.25
            revenue_accum[t] = revenue_accum[t-1] + revenue[t] if t > 0 else revenue[t]

        final_revenue[i_up, j_dn] = revenue_accum[-1]
        mean_cycles_day[i_up, j_dn] = np.mean(verify_cycles)
```

D.1.4 Heuristic: Energy and Constant Capacity participation

```
from dataclasses import dataclass
import numpy as np

@dataclass
class Battery:
    p_min_mw: float
    p_max_mw: float
    e_min_mwh: float
    e_max_mwh: float
```

```python
    eff_charge: float
    eff_discharge: float
    max_cycles_per_day: float

@dataclass
class Capacity:
    cap_min_mw: float
    cap_max_mw: float
    step: float

def simulate_battery_strategy_1(
    battery: Battery,
    capacity_conf: Capacity,
    up_marginal_price,
    down_marginal_price,
    up_marginal_capacity_price,
    up_marginal_imbalance_price,
    n_steps,
    n_up_premiums=8,
    n_down_premiums=8
):
    n_cases = int((capacity_conf.cap_max_mw - capacity_conf.cap_min_mw) / capacity_conf.step) +
        1
    cap_values = np.linspace(capacity_conf.cap_min_mw, capacity_conf.cap_max_mw, n_cases)
    up_premium_values = np.arange(n_up_premiums)
    down_premium_values = np.arange(n_down_premiums)

    final_revenue = np.zeros((n_up_premiums, n_down_premiums, n_cases))
    mean_cycles_day = np.zeros((n_up_premiums, n_down_premiums, n_cases))
    final_revenue_cap = np.zeros((n_up_premiums, n_down_premiums, n_cases))
    final_capacity_cost = np.zeros((n_up_premiums, n_down_premiums, n_cases))

    for idx_case, cap in enumerate(cap_values):
        for i_up, up_p in enumerate(up_premium_values):
            for j_dn, dn_p in enumerate(down_premium_values):
                e_current = battery.e_max_mwh / 2
                revenue = np.zeros(n_steps)
                revenue_accum = np.zeros(n_steps)
                capacity_cost = np.zeros(n_steps)
                revenue_capacity_accum = np.zeros(n_steps)
                cycles_per_day = np.zeros(n_steps)

                for t in range(n_steps):
                    cheap_down_threshold = 0 if t < 2 else
                        np.percentile(down_marginal_price[:t-1], 25)
                    if t < 8:
                        up_price = np.min(up_marginal_price[:t+1]) + up_p
                        down_price = np.max(down_marginal_price[:t+1]) - dn_p
                    else:
                        up_price = np.min(up_marginal_price[t-8:t]) + up_p
                        down_price = np.max(down_marginal_price[t-8:t]) - dn_p

                    up_volume = min(battery.p_max_mw, max(cap, e_current * 4 *
                        battery.eff_discharge))
                    down_volume = min(battery.p_max_mw, (battery.e_max_mwh - e_current) * 4 /
                        battery.eff_charge)

```

```
                    p_up = up_volume if up_price <= up_marginal_price[t] else 0
                    p_dn = down_volume if down_price >= down_marginal_price[t] else 0

                    if p_up and p_dn:
                        p_dn = 0

                    p_set = p_dn - p_up
                    e_inter = 0
                    if e_current - p_up * 0.25 < cap * 0.25 / battery.eff_discharge and p_set < 0:
                        e_inter = cap * 0.25 / battery.eff_discharge - (e_current - p_up * 0.25 / battery.eff_discharge)
                        capacity_cost[t] = up_marginal_imbalance_price[t] * e_inter

                    p_mw = p_set + e_inter * 4
                    e_current = np.clip(
                        e_current + (max(p_set, 0) * battery.eff_charge + min(p_set, 0) / battery.eff_discharge) * 0.25 + e_inter,
                        battery.e_min_mwh,
                        battery.e_max_mwh
                    )

                    cycles_per_day[t] = -p_mw * 0.25 / (battery.e_max_mwh * battery.eff_discharge) if p_mw < 0 else 0
                    verify_cycles = np.sum(cycles_per_day[max(0, t-95):t+1])

                    revenue[t] = (
                        p_up * up_marginal_price[t] - p_dn * down_marginal_price[t]
                    ) * 0.25 + cap * up_marginal_capacity_price[t] * 0.25 - capacity_cost[t]
                    revenue_accum[t] = revenue_accum[t-1] + revenue[t] if t > 0 else revenue[t]
                    revenue_capacity_accum[t] = revenue_capacity_accum[t-1] + cap * up_marginal_capacity_price[t] * 0.25 if t > 0 else cap * up_marginal_capacity_price[t] * 0.25

                final_revenue[i_up, j_dn, idx_case] = revenue_accum[-1]
                mean_cycles_day[i_up, j_dn, idx_case] = np.mean(verify_cycles)
                final_revenue_cap[i_up, j_dn, idx_case] = revenue_capacity_accum[-1]
                final_capacity_cost[i_up, j_dn, idx_case] = np.sum(capacity_cost)

    return final_revenue, mean_cycles_day, final_revenue_cap, final_capacity_cost, cap_values

# Example setup
battery_1h = Battery(1, 1, 0, 1, 0.85, 1, 2.0)
battery_2h = Battery(1, 1, 0, 2, 0.85, 1, 2.0)
battery_4h = Battery(1, 1, 0, 4, 0.85, 1, 2.0)
capacity_conf = Capacity(0.0, 1.0, 0.05)
n_steps = x
```

D.1.5 Adaptive Strategy: Optimized Capacity and Price Premium Based on Previous 3 Days

```
from dataclasses import dataclass
import numpy as np
import pandas as pd

@dataclass
class Battery:
```

```
    p_min_mw: float
    p_max_mw: float
    e_min_mwh: float
    e_max_mwh: float
    eff_charge: float
    eff_discharge: float
    max_cycles_per_day: float

@dataclass
class Capacity:
    cap_min_mw: float
    cap_max_mw: float
    step: float

battery_1h = Battery(
    p_min_mw=1.0,
    p_max_mw=1.0,
    e_min_mwh=0.0,
    e_max_mwh=1.0,
    eff_charge=0.85,
    eff_discharge=1.0,
    max_cycles_per_day=2.0
)

battery_2h = Battery(
    p_min_mw=1.0,
    p_max_mw=1.0,
    e_min_mwh=0.0,
    e_max_mwh=2.0,
    eff_charge=0.85,
    eff_discharge=1.0,
    max_cycles_per_day=2.0
)

capacity_2h = Capacity(
    cap_min_mw=0.0,
    cap_max_mw=1.0,
    step=0.05
)

n_steps = 3020

e_current_mwh = battery_2h.e_max_mwh * 0.5
p_mw = np.zeros(n_steps)
e_mwh = np.zeros(n_steps)
cycles_per_day = np.zeros(n_steps)
verify_cycles_per_day = np.zeros(n_steps)
p_set_mw = np.zeros(n_steps)
e_intermediate = np.zeros(n_steps)
p_up_mw = np.zeros(n_steps)
p_down_mw = np.zeros(n_steps)

revenue = np.zeros(n_steps)
revenue_accum = np.zeros(n_steps)
up_bid_price = np.zeros(n_steps)
down_bid_price = np.zeros(n_steps)
up_bid_volume = np.zeros(n_steps)
```

```
down_bid_volume = np.zeros(n_steps)
cost_charge = np.zeros(n_steps)

capacity_cost = np.zeros(n_steps)
e_no_imbalance = np.zeros(n_steps)
e_threshold = np.zeros(n_steps)
revenue_capacity = np.zeros(n_steps)
final_revenue_capacity = np.zeros(n_steps)
revenue_accum_capacity = np.zeros(n_steps)

n_cases = int((capacity_2h.cap_max_mw - capacity_2h.cap_min_mw) / capacity_2h.step) + 1
capacity_cases = np.zeros(n_cases)

n_premiums = int(up_percentiles[3] - up_percentiles[1])
up_premiums = np.zeros(n_steps)
down_premiums = np.zeros(n_steps)

revenue_matrix = np.zeros((n_premiums, n_cases))
cheap_down_threshold = np.zeros(n_steps)
counter = 0
flag = 0

for m in range(n_steps):
    if time_20_00_vector[m] == 1 or flag == 1:
        flag = 0
        counter = 0
        for x in range(n_premiums):
            up_premiums[x] = x * 3
            down_premiums[x] = x * 1
            for n in range(n_cases):
                capacity_cases[n] = capacity_2h.cap_min_mw + n * capacity_2h.step
                for qh in range(max(1, m - 96), m):
                    if qh < 8:
                        up_bid_price[qh] = np.min(up_marginal_price[:qh+1]) + up_premiums[x]
                        down_bid_price[qh] = np.max(down_marginal_price[:qh+1]) - down_premiums[x]
                    else:
                        up_bid_price[qh] = np.min(up_marginal_price[qh-8:qh]) + up_premiums[x]
                        down_bid_price[qh] = np.max(down_marginal_price[qh-8:qh]) -
                            down_premiums[x]

                    up_bid_volume[qh] = min(battery_2h.p_max_mw,
                                            max(capacity_cases[n], e_mwh[qh-1] * 4 *
                                                battery_2h.eff_discharge))
                    down_bid_volume[qh] = min(battery_2h.p_max_mw,
                                              (battery_2h.e_max_mwh - e_mwh[qh-1]) * 4 /
                                                  battery_2h.eff_charge)

                    if up_bid_price[qh] <= up_marginal_price[qh] and up_bid_volume[qh] > 0:
                        p_up_mw[qh] = up_bid_volume[qh]
                    elif down_bid_price[qh] >= down_marginal_price[qh] and down_bid_volume[qh] >
                        0:
                        p_down_mw[qh] = down_bid_volume[qh]

                    if p_up_mw[qh] > 0:
                        p_down_mw[qh] = 0
                    elif p_down_mw[qh] > 0:
                        p_up_mw[qh] = 0
```

```
                    p_set_mw[qh] = p_down_mw[qh] - p_up_mw[qh]
                    e_no_imbalance[qh] = e_mwh[qh-1] - p_up_mw[qh] * 0.25
                    e_threshold[qh] = capacity_cases[n] * 0.25 / battery_2h.eff_discharge

                    if e_no_imbalance[qh] < e_threshold[qh] and p_set_mw[qh] < 0:
                        e_intermediate[qh] = e_threshold[qh] - (e_mwh[qh-1] - p_up_mw[qh] * 0.25)
                        capacity_cost[qh] = up_marginal_imbalance_price[qh] * e_intermediate[qh]
                    else:
                        e_intermediate[qh] = 0

                    p_mw[qh] = p_set_mw[qh] + e_intermediate[qh] * 4
                    e_current = e_mwh[qh-1] + \
                        (max(p_set_mw[qh], 0) * battery_2h.eff_charge + min(p_set_mw[qh], 0) / battery_2h.eff_discharge) * 0.25 + e_intermediate[qh]
                    e_current = max(min(e_current, battery_2h.e_max_mwh), battery_2h.e_min_mwh)

                    if p_mw[qh] < 0:
                        cycles_per_day[qh] = -p_mw[qh] * 0.25 / (battery_2h.e_max_mwh * battery_2h.eff_discharge)
                    else:
                        cycles_per_day[qh] = 0

                    verify_cycles_per_day[qh] = np.sum(cycles_per_day[max(0, qh-95):qh+1])

                    e_mwh[qh] = e_current
                    revenue[qh] = (p_up_mw[qh] * up_marginal_price[qh] - p_down_mw[qh] * down_marginal_price[qh]) * 0.25 + \
                                 capacity_cases[n] * up_marginal_capacity_price[qh] * 0.25 - capacity_cost[qh]
                    revenue_capacity[qh] = capacity_cases[n] * up_marginal_capacity_price[qh] * 0.25
                    final_revenue_capacity[qh] = revenue_capacity[qh] - capacity_cost[qh]
                    revenue_accum[qh] = revenue_accum[qh-1] + revenue[qh] if qh > 0 else revenue[qh]

                revenue_matrix[x, n] = revenue_accum[m-1]

            best_x, best_n = np.unravel_index(np.argmax(revenue_matrix, axis=None), revenue_matrix.shape)
            optimal_capacity = capacity_cases[best_n]
            optimal_up_premium = best_x * 3
            optimal_down_premium = best_x * 1

            for f in range(m, min(m + 96, n_steps)):
                capacity_cases[f] = optimal_capacity
                up_premiums[f] = optimal_up_premium
                down_premiums[f] = optimal_down_premium

    counter += 1
    if counter == 96:
        flag = 1
    # Additional simulation steps continue here...
```

D.1.6 Adaptive Strategy: Hourly Optimized Capacity and Price Premium Based on the Previous Day

```
from dataclasses import dataclass
import numpy as np
import pandas as pd

@dataclass
class Battery:
    p_min_mw: float
    p_max_mw: float
    e_min_mwh: float
    e_max_mwh: float
    eff_charge: float
    eff_discharge: float
    max_cycles_per_day: float

@dataclass
class Capacity:
    cap_min_mw: float
    cap_max_mw: float
    step: float

battery_2h = Battery(
    p_max_mw=1.0,
    p_min_mw=1.0,
    e_min_mwh=0.0,
    e_max_mwh=4.0,
    eff_charge=0.85,
    eff_discharge=1.0,
    max_cycles_per_day=2.0
)
capacity_2h = Capacity(cap_min_mw=0.0, cap_max_mw=1.0, step=0.05)

n_steps = 1500

e_current_mwh = battery_2h.e_max_mwh * 0.5
p_mw = np.zeros(n_steps)
e_mwh = np.zeros(n_steps)
cycles_per_day = np.zeros(n_steps)
verify_cycles_per_day = np.zeros(n_steps)
p_set_mw = np.zeros(n_steps)
p_up_mw = np.zeros(n_steps)
p_down_mw = np.zeros(n_steps)

revenue = np.zeros(n_steps)
revenue_accum = np.zeros(n_steps)
up_bid_price = np.zeros(n_steps)
down_bid_price = np.zeros(n_steps)
up_bid_volume = np.zeros(n_steps)
down_bid_volume = np.zeros(n_steps)
cost_charge = np.zeros(n_steps)

capacity_cost = np.zeros(n_steps)
e_no_imbalance = np.zeros(n_steps)
e_threshold = np.zeros(n_steps)
revenue_capacity = np.zeros(n_steps)
```

```
final_revenue_capacity = np.zeros(n_steps)
revenue_accum_capacity = np.zeros(n_steps)

capacity_per_hour = np.zeros(24)
up_premium_per_hour = np.zeros(24)
down_premium_per_hour = np.zeros(24)

cheap_down_threshold = np.zeros(n_steps)
counter = 0
flag = 0

for m in range(n_steps):
    if time_20_00_vector[m] == 1 or flag == 1:
        flag = 0
        counter = 0
        n_cases = int((capacity_2h.cap_max_mw - capacity_2h.cap_min_mw) / capacity_2h.step) + 1
        cap_range = np.linspace(capacity_2h.cap_min_mw, capacity_2h.cap_max_mw, n_cases)
        n_premium = int(up_percentiles[3] - up_percentiles[1])
        up_premium_range = np.array([i * 3 for i in range(n_premium)])
        down_premium_range = np.array([i for i in range(n_premium)])

        for h in range(24):
            best_revenue = -np.inf
            best_cap = 0.0
            best_up_premium = 0.0
            best_down_premium = 0.0

            start_step = m - 96 + h * 4
            end_step = start_step + 4

            for idx in range(n_cases):
                cap_test = cap_range[idx]
                for x in range(n_premium):
                    up_prem = up_premium_range[x]
                    down_prem = down_premium_range[x]
                    e_tmp = e_mwh[start_step-1] if start_step > 0 else battery_2h.e_max_mwh * 0.5
                    revenue_sum = 0.0

                    for qh in range(start_step, end_step):
                        if qh < 0 or qh >= m:
                            continue
                        if qh < 8:
                            up_price = min(up_marginal_price[:qh+1]) + up_prem
                            down_price = max(down_marginal_price[:qh+1]) - down_prem
                        else:
                            up_price = min(up_marginal_price[qh-8:qh]) + up_prem
                            down_price = max(down_marginal_price[qh-8:qh]) - down_prem

                        up_vol = min(battery_2h.p_max_mw, max(cap_test, e_tmp * 4 *
                            battery_2h.eff_discharge))
                        down_vol = min(battery_2h.p_max_mw, (battery_2h.e_max_mwh - e_tmp) * 4 /
                            battery_2h.eff_charge)

                        p_up = up_vol if up_price <= up_marginal_price[qh] and up_vol > 0 else 0
                        p_down = down_vol if down_price >= down_marginal_price[qh] and down_vol >
                            0 else 0

```

```
                        if p_up > 0:
                            p_down = 0
                        elif p_down > 0:
                            p_up = 0

                        revenue_qh = (p_up * up_marginal_price[qh] - p_down * down_marginal_price[qh]) * 0.25 + cap_test * up_marginal_capacity_price[qh] * 0.25
                        revenue_sum += revenue_qh

                        e_tmp += (max(p_up, 0) * battery_2h.eff_charge + min(p_up, 0) / battery_2h.eff_discharge) * 0.25
                        e_tmp = max(min(e_tmp, battery_2h.e_max_mwh), battery_2h.e_min_mwh)

                    if revenue_sum > best_revenue:
                        best_revenue = revenue_sum
                        best_cap = cap_test
                        best_up_premium = up_prem
                        best_down_premium = down_prem

            capacity_per_hour[h] = best_cap
            up_premium_per_hour[h] = best_up_premium
            down_premium_per_hour[h] = best_down_premium

        for f in range(m, min(m + 96, len(time_20_00_vector))):
            hour_idx = (f - m) // 4
            capacity[f] = capacity_per_hour[hour_idx]
            up_premium[f] = up_premium_per_hour[hour_idx]
            down_premium[f] = down_premium_per_hour[hour_idx]

    counter += 1
    if counter == 96:
        flag = 1

    if m > 1:
        cheap_down_threshold[m] = np.percentile(down_marginal_price[:m-1], 25)
    if m < 8:
        up_bid_price[m] = min(up_marginal_price[:m+1]) + up_premium[m]
        down_bid_price[m] = max(down_marginal_price[:m+1]) - down_premium[m]
    else:
        up_bid_price[m] = min(up_marginal_price[m-8:m]) + up_premium[m]
        down_bid_price[m] = max(down_marginal_price[m-8:m]) - down_premium[m]

    if m > 1:
        if e_mwh[m-1] < 0.4 * battery_2h.e_max_mwh or down_marginal_price.iloc[-1] > cheap_down_threshold[m]:
            flag = 1
            down_bid_price[m] = 1000
        if np.all(e_mwh[m-13:m-1] == battery_2h.e_max_mwh):
            up_bid_price[m] = -1000
            flag = 0

    up_bid_volume[m] = min(battery_2h.p_max_mw, max(capacity[f], e_mwh[m-1] * 4 * battery_2h.eff_discharge))
    down_bid_volume[m] = min(battery_2h.p_max_mw, (battery_2h.e_max_mwh - e_mwh[m-1]) * 4 / battery_2h.eff_charge)

```

```
if m > 1:
    prev_cycles = verify_cycles_per_day[m-1]
    if prev_cycles > battery_2h.max_cycles_per_day * 1.7:
        up_bid_volume[m] *= 0.2
    elif prev_cycles > battery_2h.max_cycles_per_day * 1.5:
        up_bid_volume[m] *= 0.3
    elif prev_cycles > battery_2h.max_cycles_per_day * 1.2:
        up_bid_volume[m] *= 0.5
    elif prev_cycles > battery_2h.max_cycles_per_day * 1.15:
        up_bid_volume[m] *= 0.7

if up_bid_price[m] <= up_marginal_price[m] and up_bid_volume[m] > 0:
    p_up_mw[m] = up_bid_volume[m]
elif down_bid_price[m] >= down_marginal_price[m] and down_bid_volume[m] > 0:
    p_down_mw[m] = down_bid_volume[m]

if flag == 1:
    p_down_mw[m] = down_bid_volume[m]
    p_up_mw[m] = 0
flag = 0

if p_up_mw[m] > 0:
    p_down_mw[m] = 0
elif p_down_mw[m] > 0:
    p_up_mw[m] = 0

p_set_mw[m] = p_down_mw[m] - p_up_mw[m]

e_no_imbalance[m] = e_mwh[m-1] - p_up_mw[m] * 0.25
e_threshold[m] = capacity[f] * 0.25 / battery_2h.eff_discharge

if e_no_imbalance[m] < e_threshold[m] and p_set_mw[m] < 0:
    e_intermediate[m] = e_threshold[m] - (e_mwh[m-1] - p_up_mw[m] * 0.25)
    capacity_cost[m] = up_marginal_imbalance_price[m] * e_intermediate[m]
else:
    e_intermediate[m] = 0

p_mw[m] = p_set_mw[m] + e_intermediate[m] * 4
e_current_mwh = (
    e_mwh[m-1] +
    (max(p_set_mw[m], 0) * battery_2h.eff_charge + min(p_set_mw[m], 0) / battery_2h.eff_discharge) * 0.25 +
    e_intermediate[m]
)
e_current_mwh = max(min(e_current_mwh, battery_2h.e_max_mwh), battery_2h.e_min_mwh)

if p_mw[m] < 0:
    cycles_per_day[m] = -p_mw[m] * 0.25 / (battery_2h.e_max_mwh * battery_2h.eff_discharge)
else:
    cycles_per_day[m] = 0

if m < 96:
    verify_cycles_per_day[m] = sum(cycles_per_day[:m+1])
else:
    verify_cycles_per_day[m] = sum(cycles_per_day[m-95:m+1])

e_mwh[m] = e_current_mwh
```

```
    revenue[m] = (
        p_up_mw[m] * up_marginal_price[m]
        - p_down_mw[m] * down_marginal_price[m]
    ) * 0.25 + cap[f] * up_marginal_capacity_price[m] * 0.25 - capacity_cost[m]
    revenue_capacity[m] = cap[f] * up_marginal_capacity_price[m] * 0.25
    final_revenue_capacity[m] = revenue_capacity[m] - capacity_cost[m]
    cost_charge[m] = p_down_mw[m] * down_marginal_price[m]

    if m > 0:
        revenue_accum[m] = revenue_accum[m-1] + revenue[m]
        revenue_accum_capacity[m] = revenue_accum_capacity[m-1] + revenue_capacity[m]
    else:
        revenue_accum[m] = revenue[m]
        revenue_accum_capacity[m] = revenue_capacity[m]
```

D.2 DAH: Model Revenue

```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_squared_error
import matplotlib.pyplot as plt
import pandas as pd

def run_grouped_regression(df, group_col, label="Group"):
    df_model = df.copy()

    threshold = len(df_model) * 0.5
    df_model = df_model.dropna(axis=1, thresh=threshold)

    cols_to_drop = [
        'Hydro Run-of-River_min', 'Hydro Run-of-River_mean', 'Hydro Run-of-River_max',
        'Hydro water reservoir_min', 'Hydro water reservoir_mean', 'Hydro water reservoir_max',
        'Hydro pumped storage_min', 'Hydro pumped storage_mean', 'Hydro pumped storage_max',
        'Hydro pumped storage consumption_min', 'Hydro pumped storage consumption_mean',
        'Hydro pumped storage consumption_max',
        'Load_min_x', 'Load_mean_x', 'Load_max_x',
        'Period Start_min', 'Period Start_mean', 'Period Start_max',
        'Nuclear_min_x', 'Nuclear_mean_x', 'Nuclear_max_x',
        'Residual load_min_x', 'Residual load_mean_x', 'Residual load_max_x',
        'Fossil brown coal / lignite_min', 'Fossil brown coal / lignite_mean', 'Fossil brown
            coal / lignite_max',
        'Fossil hard coal_min', 'Fossil hard coal_mean', 'Fossil hard coal_max',
        'Fossil oil_min', 'Fossil oil_mean', 'Fossil oil_max',
        'Fossil gas_min', 'Fossil gas_mean', 'Fossil gas_max',
        'Biomass_min', 'Biomass_mean', 'Biomass_max',
        'Geothermal_min', 'Geothermal_mean', 'Geothermal_max',
        'Marine_min', 'Marine_mean', 'Marine_max',
        'Other renewables_min', 'Other renewables_mean', 'Other renewables_max',
        'Waste_min', 'Waste_mean', 'Waste_max',
        'Others_min', 'Others_mean', 'Others_max',
        'Solar_min_x', 'Solar_mean_x', 'Solar_max_x',
        'Wind onshore_min_x', 'Wind onshore_mean_x', 'Wind onshore_max_x',
        'CO2 Price',
        'Day_min', 'Day_mean', 'Day_max',
        'Fossil',
        'Year_min', 'Year_mean', 'Year_max',
```

```
        ’OtherRenewables’, ’Max_Price’, ’Avg_Price’, ’Min_Price’,
        ’Renewable share of generation_max’, ’Renewable share of generation_min’,
        ’Renewable share of load_max’, ’Renewable share of load_min’
    ]
    df_model = df_model.drop(columns=cols_to_drop, errors=’ignore’)

    df_model = df_model.select_dtypes(include=[’float64’, ’int64’])
    df_model = df_model.dropna()

    groups = sorted(df[group_col].dropna().unique())

    for g in groups:
        df_group = df_model[df[group_col] == g]

        if len(df_group) < 50:
            print(f"\n{label} ’{g}’ has too few samples ({len(df_group)}), skipping.")
            continue

        X = df_group.drop(columns=’Revenue’, errors=’ignore’)
        y = df_group[’Revenue’]

        X_train, X_test, y_train, y_test = train_test_split(
            X, y, test_size=0.2, random_state=42
        )

        model = LinearRegression()
        model.fit(X_train, y_train)

        y_pred = model.predict(X_test)
        r2 = r2_score(y_test, y_pred)
        mse = mean_squared_error(y_test, y_pred)

        print(f"\n{label}: {g}")
        print(f" R: {r2:.3f}")
        print(f" MSE: {mse:.2f}")

        plt.figure(figsize=(5, 5))
        plt.scatter(y_test, y_pred, alpha=0.5)
        plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], ’r--’)
        plt.xlabel(’Actual Revenue’)
        plt.ylabel(’Predicted Revenue’)
        plt.title(f’Actual vs Predicted - {label}: {g}’)
        plt.grid(True)
        plt.tight_layout()
        plt.show()

        coef_df = pd.DataFrame({
            ’Variable’: X.columns,
            ’Coefficient’: model.coef_
        }).sort_values(by=’Coefficient’, key=abs, ascending=False).head(8)

        plt.figure(figsize=(8, 4))
        plt.barh(coef_df[’Variable’], coef_df[’Coefficient’])
        plt.title(f’Top 8 Influential Variables - {label}: {g}’)
        plt.xlabel(’Coefficient’)
        plt.gca().invert_yaxis()
        plt.grid(axis=’x’, linestyle=’--’, alpha=0.5)
```

```
        plt.subplots_adjust(left=0.35)
        plt.tight_layout()
        plt.show()


run_grouped_regression(df_master_season, group_col='Season', label='Season')
run_grouped_regression(df_master_month, group_col='Month', label='Month')
```

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