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MASTER THESIS
Multi-Market Optimisation Model for Energy Storage
System Application

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Abstract

The accelerating deployment of intermittent renewable energy sources such as solar and wind has introduced significant challenges in maintaining grid stability and efficient electricity market operations. One of the key problems is the **temporal misalignment between electricity generation and consumption**, which creates both technical imbalances in the power system and economic inefficiencies in electricity markets. Battery Energy Storage Systems (BESS) offer a promising solution by providing flexibility, however, their **profitability remains uncertain** due to volatile market conditions, complex participation rules, and degradation costs. Furthermore, most existing approaches focus on single-market participation, overlooking the full economic potential of BESS in multi-market settings.

This thesis addresses that gap by developing a **multi-market optimization model** tailored for BESS operating in Belgium, where storage operators can simultaneously access arbitrage (Day-Ahead and Imbalance) and ancillary service markets (FCR, aFRR and Imbalance). The proposed model is implemented in Pyomo using mixed-integer linear programming and captures operational constraints, efficiency losses, and degradation effects under multiple cycling scenarios. It operates at 15-minute resolution and dynamically allocates capacity across markets to maximize total revenue.

Market data from Elia covering the year 2024 was used to simulate real-world operation, while data after Belgium's integration into the PICASSO platform was excluded due to fundamental changes in aFRR pricing and structure. The analysis reveals that a coordinated multi-market strategy improves profitability over isolated market participation, with ancillary services providing stable revenue and arbitrage exploiting price volatility. Seasonal and temporal revenue patterns were analyzed, showing clear complementarities between markets.

The analysis shows that strategic market participation can improve BESS profitability, yet outcomes are highly dependent on market volatility and policy developments. The thesis concludes by highlighting model limitations and recommending future work on integrating price forecasting and reinforcement learning for adaptive bidding strategies.

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Special thanks go to Georges Pantalos, at AdaAI, whose deep technological insights proved invaluable when I encountered challenging programming obstacles. His knowhow, proposals for model design, and sharing of best practices in software development helped me overcome numerous technical hurdles throughout the implementation of the optimisation models.

I also acknowledge Elia Group for providing access to the comprehensive market data that formed the backbone of this analysis. The availability of high-quality, real-world data on Belgian electricity markets through their open data platform was essential for conducting meaningful research that reflects actual market conditions.

This thesis represents not just my individual effort, but the collective contribution of all these remarkable individuals and institutions. Any remaining errors or shortcomings are entirely my own responsibility.

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List of Abbreviations

0.1 List of Abbreviations

Abbreviation	Definition
aFRR	Automatic Frequency Restoration Reserve
BESS	Battery Energy Storage System
BRP	Balance Responsible Party
BSP	Balancing Service Provider
BTM	Behind-the-Meter
CBMP	Cross-Border Marginal Pricing
CET	Central European Time
DAM	Day-Ahead Market
DAP	Day-Ahead Pricing
ENTSO-E	European Network of Transmission System Operators for Electricity
EPEX	European Power Exchange
ESS	Energy Storage System
FCR	Frequency Containment Reserve
FTM	Front-of-the-Meter
LCOE	Levelized Cost of Energy
MARI	Manually Activated Reserves Initiative
mFRR	Manual Frequency Restoration Reserve
MILP	Mixed-Integer Linear Programming
MW	Megawatt
MWh	Megawatt hour
PICASSO	Platform for the International Coordination of Automated Frequency Restoration and Stable System Operation
PV	Photovoltaic
SIDC	Single Intraday Coupling
SoC	State of Charge
TSO	Transmission System Operator

Chapter 1

Introduction

Over the past decades, renewable energy technologies have been deployed worldwide, significantly increasing the share of green electricity and reducing reliance on fossil fuels. However, the intermittent nature of renewable sources creates challenges in balancing electricity production and consumption. Grid operators like Belgium's Elia Group must effectively manage grid flexibility to prevent energy losses and infrastructure damage while maintaining system stability.

This master's thesis explores an innovative approach to enhancing grid flexibility through energy storage technologies, specifically focusing on optimizing business opportunities in battery energy storage systems (BESS) across multiple electricity markets.

1.1 Objective and Scope

The primary objective of this thesis is to develop and analyze a multi-market optimization strategy for energy storage companies to maximize revenue streams while contributing to grid stability. The research focuses on two key electricity markets:

1. **Energy Arbitrage Markets:** Optimizing charge/discharge decisions to buy electricity at low prices and sell when prices are high
2. **Ancillary Services Markets:** Providing grid stabilization services such as frequency regulation and fast response power to system operators

Figure 1.1 illustrates the market structure and participation strategies analyzed in this study.

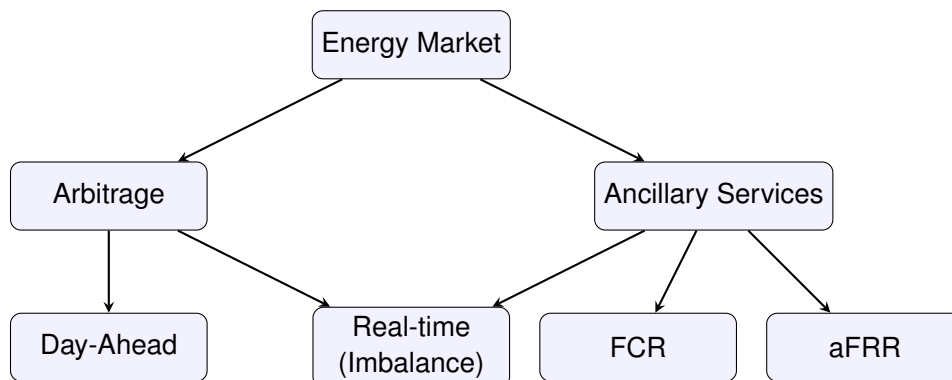


Figure 1.1: Energy market categories and participation strategies

1.2 Market Context

The optimization model operates across multiple electricity market mechanisms in Belgium, each offering distinct revenue opportunities. These markets include energy arbitrage (day-ahead and imbalance markets) and ancillary services (FCR and aFRR), with detailed market definitions and operational characteristics provided in the Background chapter.

1.3 Optimization Framework

The optimization model is designed to maximize revenues from battery storage systems through strategic participation in multiple electricity markets. The framework incorporates three key components:

1.3.1 Decision Variables

The model makes quarter-hourly decisions based on real-time market conditions, optimizing:

- **Charging Strategy:** When and how much to charge based on electricity price forecasts while respecting capacity and operational constraints
- **Discharging Strategy:** When and how much to discharge to maximize revenue while considering battery degradation
- **Market Allocation:** Dynamic selection between energy arbitrage and ancillary services based on profitability analysis

1.3.2 Operational Constraints

To ensure realistic and sustainable operations, the model incorporates:

- **Physical Constraints:** Battery capacity limits, charge/discharge rate limitations, and state-of-charge boundaries
- **Degradation Modeling:** Cycle life optimization considering battery chemistry, temperature effects, and depth-of-discharge impacts
- **Regulatory Compliance:** Market participation rules, grid codes, and ancillary service requirements
- **Economic Constraints:** CAPEX and OPEX considerations for long-term profitability assessment

1.3.3 Business Case Analysis

The model provides comprehensive business case evaluation through:

- **Revenue Optimization:** Multi-market revenue stream maximization across different time horizons
- **Sensitivity Analysis:** Impact assessment of market volatility, battery costs, and regulatory changes on profitability

- **Investment Viability:** Break-even analysis, payback period calculation, and critical threshold identification
- **Risk Assessment:** Market price volatility, technology risk, and regulatory uncertainty quantification

Chapter 2

Background and Review of the State of the Art

2.1 Background

2.1.1 Battery Energy Storage Systems in Multi-Market Environments

Battery Energy Storage Systems (BESS) have emerged as critical infrastructure for modern electricity grids, particularly in the context of renewable energy integration and grid stability [33]. These systems provide unique flexibility by enabling time-shifting of energy consumption and generation, while simultaneously offering multiple grid services across various market segments.

The European battery storage market has experienced unprecedented growth, with 17.2 GWh of new capacity installed in 2023, representing a 94% year-on-year increase [33]. This growth is driven by increasing renewable energy penetration, the need for grid flexibility, and improving battery economics. BESS applications can be broadly categorized into front-of-the-meter (FTM) and behind-the-meter (BTM) deployments, with this research focusing on FTM applications that participate directly in electricity markets.

2.1.2 Belgian Electricity Market Framework

The Belgian electricity market operates within the broader European framework, coordinated by transmission system operator Elia. The market structure enables BESS operators to participate across multiple submarkets simultaneously, creating opportunities for revenue optimization through market stacking strategies. This multi-market approach allows BESS to provide different services across various temporal scales, from real-time frequency support to day-ahead energy arbitrage.

Belgium's integration into European market coupling mechanisms ensures price convergence with neighboring countries while maintaining specific national characteristics. The regulatory framework supports innovative storage technologies through market design that recognizes the dual nature of BESS as both consumers and producers of electricity.

2.1.3 Market Participants and Definitions

Understanding the roles and responsibilities of different market participants is essential for comprehending how BESS operators can participate in Belgian electricity markets. This section provides comprehensive definitions of key market participants and their functions.

Market Participants

Transmission System Operator (TSO): Elia serves as Belgium's TSO, responsible for maintaining grid stability, coordinating electricity transmission, and managing the real-time balance between supply and demand. The TSO operates and maintains the high-voltage transmission network and ensures system security through various balancing mechanisms and reserve procurement.

Balance Responsible Parties (BRPs): BRPs are entities responsible for maintaining the balance between electricity generation, consumption, and commercial transactions within their portfolios. They submit detailed schedules to the TSO outlining their planned energy injections and withdrawals. Any deviations from these schedules trigger imbalance settlements, where BRPs receive financial rewards or penalties based on the prevailing imbalance price. BRPs engage in energy trading by purchasing electricity at lower prices and selling it at higher prices, participating in both day-ahead and real-time arbitrage markets.

Balancing Service Providers (BSPs): BSPs help maintain electricity grid stability by providing flexibility services to the TSO. They can be either Balance Responsible Parties or third parties, with their primary role being to stabilize frequency control by injecting or absorbing power from the grid to maintain the nominal frequency of 50 Hz. BSPs participate in reserve capacity markets, including Frequency Containment Reserve (FCR) and Automatic Frequency Restoration Reserve (aFRR), by offering flexibility that can be activated upon request by the TSO. Compensation is provided for both reserved capacity and energy delivered during activations.

2.1.4 Data Requirements

Historical market and system data for Belgium, covering the period from January 2024 to December 2024, were obtained from Elia's open data platform, ENTSO-E and other third party companies. Multiple Python APIs were developed to automate data retrieval and ensure reproducible dataset generation. Table 2.1 provides an overview of the datasets used in the optimization model. Each datasets will be analyse in the following section.

Table 2.1: Historical datasets used in the optimization model

Dataset	Source
Day-ahead electricity prices	ENTSO-E [36]
Imbalance prices	Elia [38]
Imbalance volumes	Elia [38]
Historical and forecasted electricity load	Elia [38]
Automatic Frequency Restoration Reserve (aFRR) reservation bids	Elia [38]
aFRR activation signals or Cross-Border Marginal price	TransNetBW
Frequency Containment Reserve (FCR)	Regelleistung

PICASSO (Platform for the International Coordination of Automated Frequency Restoration and Stable System Operation) is a European platform developed under the ENTSO-E framework to enable the cross-border activation of automatic Frequency Restoration Reserves (aFRR). It aims to enhance the efficiency and stability of the European power system by pooling balancing energy bids from participating transmission system operators (TSOs) and coordinating activations across borders [11]. The platform introduces new technical standards, settlement procedures, and pricing mechanisms that differ significantly from national market practices.

Note

On **November 26, 2024**, Belgium through Elia officially joined the PICASSO platform. This integration marked a fundamental shift in the aFRR market design, particularly in terms of pricing volatility, activation patterns, and cross-border bid coordination. Due to these structural changes, the post-PICASSO data exhibits significantly different characteristics compared to the pre-integration period.

To ensure analytical consistency and avoid distorting the revenue estimation model, **this study does not incorporate the post-PICASSO data**. The higher volatility and revised pricing logic would have introduced discontinuities in the simulation results. Further details on the rationale and data exclusion criteria are provided in the data preprocessing section of the Methodology chapter.

Market Timeline and Coordination

To facilitate understanding of the market structure, Figure 2.1 presents a chronological overview of the different market periods and their temporal relationships. The market timeline illustrates

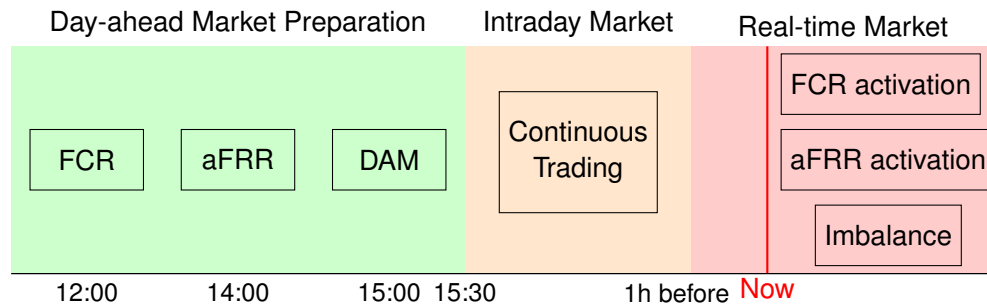


Figure 2.1: Timeline of different market operations showing the sequence from FCR and aFRR capacity reservation to day-ahead market closure and real-time imbalance settlement

how different electricity markets operate across three distinct phases: day-ahead market preparation, intraday market operations, and real-time market execution. This coordinated schedule ensures that operators can secure reserve capacity, trade energy efficiently, and respond to real-time grid needs while maintaining system stability.

The **day-ahead market preparation phase** (green zone) begins with Frequency Containment Reserve (FCR) bids, which must be submitted by 12:00 on the day ahead [15, 18]. These bids establish symmetric reserve obligations for the following day. At 14:00, providers submit their Automatic Frequency Restoration Reserve (aFRR) capacity reservation bids, specifying both upward and downward flexibility in 4-hour blocks [8, 12]. The day-ahead market closes at 15:00 through EPEX SPOT, where participants submit their day-ahead prices and capacity bids for energy arbitrage based on scheduled prices [21].

The **intraday market phase** (orange zone) operates from 15:30 until one hour before real-time through continuous trading platforms [22, 20]. This allows market participants to adjust their positions closer to delivery time, responding to updated forecasts and changing market conditions while utilizing capacity not already reserved for FCR or aFRR services [16].

During the **real-time market phase** (red zone), the system executes actual service activations and settlements. This includes FCR activation for immediate frequency response, aFRR activation based on TSO dispatch signals, and imbalance settlement for any deviations from scheduled positions [10, 13]. These real-time operations enable opportunistic energy injections or withdrawals while maintaining compliance with previously established reserve commitments.

2.1.5 Market Structure and Price Dynamics

The primary markets relevant to BESS operations in Belgium exhibit distinct characteristics and revenue opportunities:

1. Arbitrage Markets:

- **Day-Ahead Market (DAM):** Operating through hourly auctions one day before delivery, the DAM serves as the primary price discovery mechanism [1]. The market utilizes hourly price signals from EPEX SPOT, with prices published approximately 14 hours before actual delivery. Prices exhibit predictable diurnal patterns with overnight lows and evening peaks. This predictability creates clear arbitrage opportunities for BESS operations through energy time-shifting. The market operates with hourly resolution, making it suitable for strategic energy storage planning based on forecasted price patterns. Figure 2.2 displays the prices of the day-ahead market over the past five years.

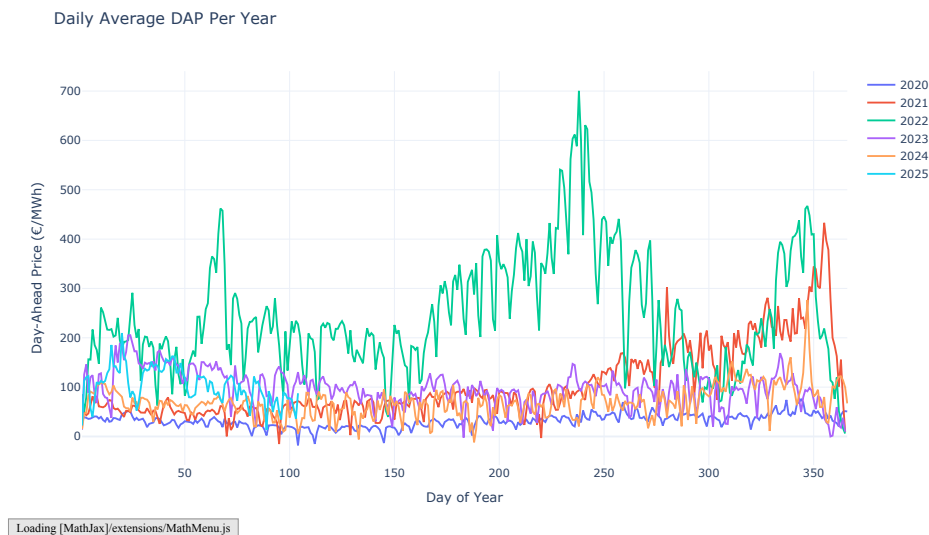


Figure 2.2: Day-ahead prices over the past five years

- **Imbalance Market:** The imbalance market corrects real-time deviations between scheduled and actual generation or consumption. While system imbalances are monitored at a 1-minute resolution, prices are settled every 15 minutes based on the aggregated imbalance during that period. Imbalance prices demonstrate significantly higher volatility than DAM prices, with price spikes frequently during periods of system stress, occurring unpredictably throughout the day. While offering potential for higher revenues, this market carries increased risk due to price volatility and activation uncertainty.
- ### 2. Ancillary Services Markets:
- Belgium participates in European-wide ancillary services procurement, with BESS particularly suited for:
- **Frequency Containment Reserve (FCR):** Primary frequency control activated automatically within 30 seconds to counteract frequency deviations from the nominal 50 Hz. Belgium participates in the FCR Cooperation platform since 2016, involving nine countries and twelve Transmission System Operators (TSOs), creating a unified FCR market that reduces overall procurement costs [14, 17]. The market operates through

daily auctions with four-hour product blocks using pay-as-cleared pricing. Capacity prices typically range between 10-25 €/MW/h with occasional peaks above 30 €/MW/h [31]. The minimum bid size is 1 MW, with gate opening at D-7 11:00 CET and closure at D-1 12:00 CET.

FCR requires symmetric capacity provision, meaning participants must offer equal amounts of upward and downward regulation capability. The service acts as an automatic emergency response system, providing immediate grid support when frequency deviations occur. Participants receive capacity payments for reserving power and additional energy payments when their reserves are activated. Figure A.7 presents the daily profile of FCR capacity and clearing prices, providing insights into their variation throughout the day.

- **Automatic Frequency Restoration Reserve (aFRR):** Secondary frequency control automatically activated by Elia through setpoint signals sent every four seconds, with full activation required within 5 minutes (reduced from 7.5 minutes as of December 2024) [9]. aFRR encompasses both capacity reservation and activation services:

aFRR Capacity Reservation: Participants commit capacity for both upward and downward regulation, with different price signals for each direction. The market requires participants to commit capacity that can be called upon by the TSO, similar to being on standby for grid support services. Revenue is generated through capacity payments for reserved power, with the optimization challenge being to identify the most profitable combination of upward and downward capacity commitments while respecting battery power and energy constraints.

Figure 2.3 illustrates the distribution of aFRR capacity reservation prices, highlighting the typical price ranges and variability faced by battery operators when optimizing their bidding strategies. Downward prices apply when the system frequency exceeds 50 Hz, while upward prices apply when the frequency falls below 50 Hz. In 2024, most downward price bids ranged between €0 and €10/MW, indicating a relatively low opportunity cost. In contrast, upward prices were more widely distributed, typically between €10 and €100/MW, reflecting greater competition among participants.

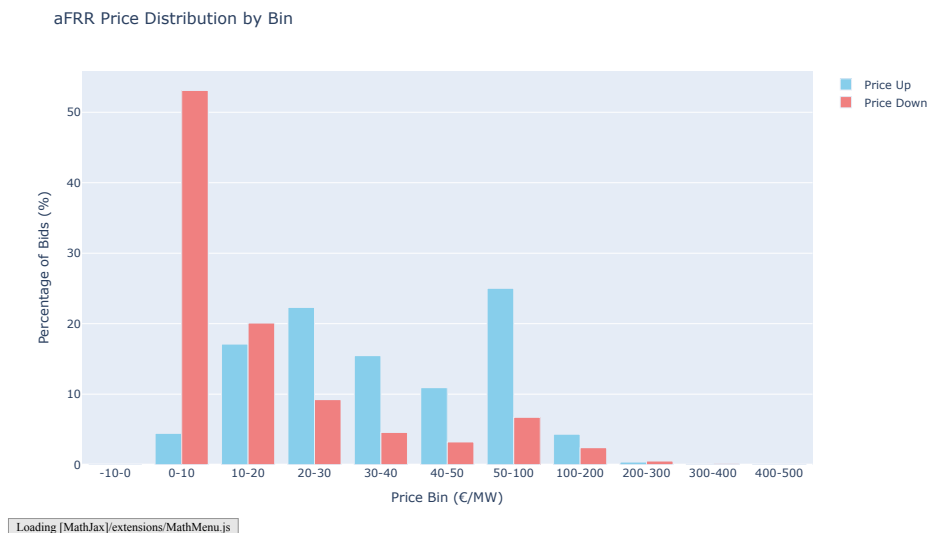


Figure 2.3: aFRR capacity reservation price distribution showing the statistical characteristics of upward and downward regulation pricing throughout the analysis period

aFRR Activation: Provides real-time energy delivery when the TSO calls upon reserved aFRR capacity to address frequency deviations. The service incorporates

high-frequency response requirements, with activation signals updated every 4 seconds based on grid conditions. The activation logic responds directly to system imbalance conditions: during power deficit periods, the battery provides upward regulation through discharging, while during excess power periods, it provides downward regulation through charging. Revenue differentiation exists between upward and downward regulation services, reflecting the different grid support values.

- **Manual Frequency Restoration Reserve (mFRR):** Tertiary control reserve manually activated by the TSO within 12.5 minutes for longer-duration imbalances when automatic reserves are insufficient. Belgium participates in the MARI (Manually Activated Reserves Initiative) platform, operational since 2022 and expanding across Europe [19]. While mFRR represents an important ancillary service market, this study excludes it from the optimization framework since energy storage technologies are not integrated into the mFRR market structure.
- **Imbalance Ancillary Service:** A secondary balancing support service during grid imbalances, operating as a complementary service to primary imbalance arbitrage with reduced activation certainty. This service leverages real-time imbalance price signals but accounts for lower activation probability (approximately 10%) due to its auxiliary role in grid balancing. The service provides risk-adjusted revenue opportunities for BESS operators who can offer additional grid support beyond their primary market commitments.

To maintain analytical consistency, this study focuses on the pre-PICASSO period using 2024 data prior to the November market transition, as the platform fundamentally changed aFRR market structure and pricing mechanisms.

Figure 2.4 illustrates the distinct price patterns across DAM, imbalance, and FCR markets for a representative day in 2024, demonstrating the complementary nature of their pricing behaviors for multi-market BESS optimization strategies.

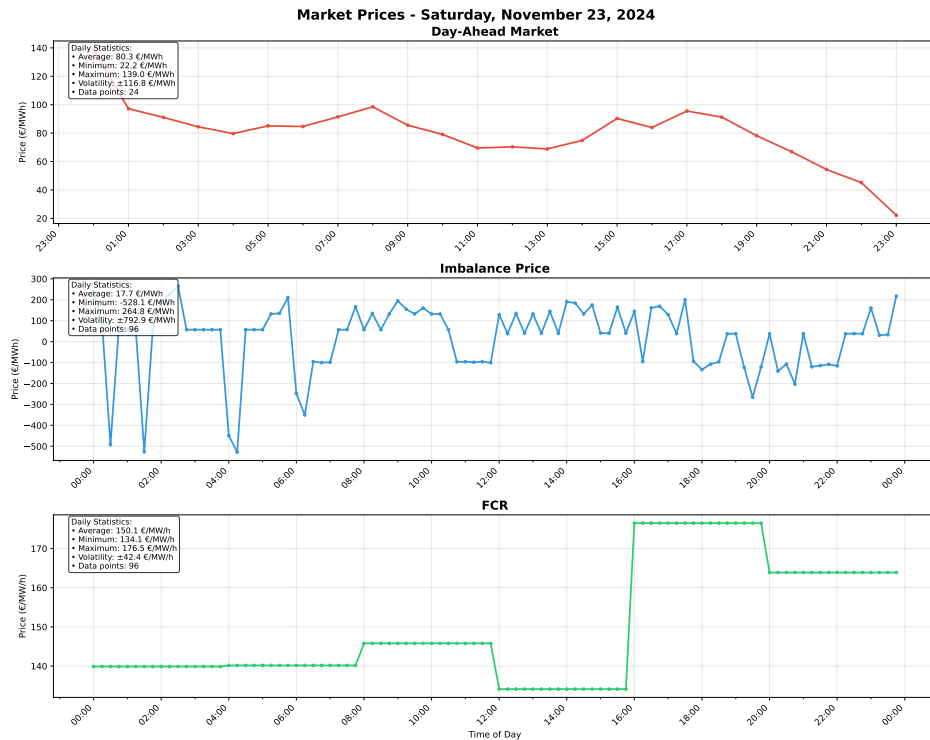


Figure 2.4: Market prices for DAM, Imbalance, and FCR markets on a representative day in 2024, showing the distinct volatility patterns and pricing dynamics across the three primary markets relevant to BESS operations

2.2 Literature Review

2.2.1 Multi-Market Optimization Frameworks

The academic literature has increasingly focused on developing optimization frameworks that enable BESS to participate across multiple electricity markets simultaneously, maximizing revenue through "stacking" different value streams.

A pioneering multi-scale optimization framework for electricity market participation was introduced, establishing mathematical foundations for coordinating decisions across different temporal scales [6]. This work demonstrated the importance of hierarchical optimization approaches when dealing with markets operating at different time intervals.

Comprehensive economic analysis of parallel revenue streams for battery storage systems has quantified the value of multi-market participation compared to single-market strategies [4]. This research showed that revenue stacking can significantly improve the business case for BESS investments, particularly in European markets.

Recent developments in Nordic markets have focused on optimal scheduling algorithms for BESS participation across spot markets and frequency reserves [25]. These approaches employ generalized additive models for price forecasting and stochastic optimization for coordinated bidding, providing insights directly applicable to similar optimization challenges in Belgian markets.

2.2.2 Advanced Simulation and Optimization Methodologies

The complexity of multi-market BESS operation has driven the development of sophisticated simulation frameworks that can accurately model the interaction between different markets and operational constraints.

A groundbreaking multi-level simulation framework has been presented that integrates day-ahead and intraday dispatch optimization with high-resolution operational simulation [35]. This approach addresses the temporal scale mismatch between market decision-making (15-minute intervals) and actual system operation (second-by-second), providing a methodology directly relevant to this thesis.

The specific value of BESS participation in continuous intraday markets has been explored through comparison of forecast-driven strategies with perfect foresight scenarios [27]. Work using German market data demonstrates the significant revenue potential of intraday trading, with forecast-driven models achieving 89% of perfect foresight revenues.

Practical insights into BESS revenue performance across three major European markets (Germany, Italy, and UK) have shown how market-specific characteristics affect optimal operational strategies, highlighting the importance of location-specific optimization approaches [34].

2.2.3 Degradation-Aware Operation

A critical aspect of BESS optimization is accounting for battery degradation, which directly impacts both operational decisions and long-term profitability. The literature has developed several approaches to incorporate degradation considerations into optimization frameworks.

Ageing and efficiency aware dispatch algorithms have been developed using mixed integer linear programming, incorporating both calendar and cycle ageing effects [26]. This work established methodological foundations for degradation-aware optimization that consider the trade-off between immediate revenue and long-term asset value.

The challenge of balancing immediate revenue optimization with degradation costs has been

extensively studied, with researchers developing various approaches ranging from simple cycle counting to complex electrochemical models. The choice of degradation modeling approach significantly impacts optimization results and computational complexity.

2.2.4 Research Gaps and Methodological Contributions

While the literature provides strong foundations for multi-market BESS optimization, several gaps remain that this thesis addresses:

1. **Belgian Market Specificity:** Limited research has specifically addressed the unique characteristics of Belgian electricity markets and their regulatory framework.
2. **Integrated Multi-Market Analysis:** Most studies focus on individual markets or simplified multi-market scenarios, rather than comprehensive optimization across all relevant Belgian market segments.
3. **Practical Implementation:** There is a need for optimization frameworks that can be practically implemented by market participants, balancing computational complexity with solution quality.
4. **Uncertainty Quantification:** Limited research addresses the impact of price forecasting errors and market uncertainties on optimal BESS operation strategies.

This thesis builds upon the established methodological foundations while addressing these specific gaps through the development of a comprehensive optimization framework tailored to Belgian market conditions and validated through extensive scenario analysis.

Chapter 3

Methodology

The development of the optimization model follows an incremental approach, beginning with individual market stream analysis before integrating multiple markets. This methodology starts by studying each electricity market separately to understand how a battery can make profit, then combines everything into one complete system. This approach ensures a comprehensive understanding of each market's economic potential for Energy Storage System (ESS) participation in the Belgian electricity market. The initial phase focuses on establishing baseline models for each market segment, which will later serve as the foundation for a more sophisticated multi-market optimization model.

3.1 Preprocessing Stage

Prior to the optimization stage, comprehensive data preprocessing was conducted to ensure data quality, handle missing values, and identify outliers. While the datasets were obtained through API functions, they required significant preprocessing to address various data quality issues. The following key preprocessing steps were implemented:

- The day-ahead market dataset required header standardization to organize data properly and ensure consistent column naming conventions across the analysis.
- The FCR and aFRR datasets presented challenges with missing timestamps and NaN values. These NaN values represented periods of non-participation in the market, distinct from zero values which would indicate active participation. To address this, a specific constraint was implemented to exclude NaN values from the participation analysis rather than replacing them with zeros.
- A significant market change occurred when Belgium joined the PICASSO market on November 26, 2024, resulting in substantial changes to aFRR activation prices and volumes, as figure 3.1 shows. To maintain consistency in the analysis of annual revenue streams, the post-PICASSO data was excluded from the analysis, focusing instead on the established price patterns from the pre-PICASSO period.

3.2 Battery Model Parameters

The battery optimization model incorporates several key parameters that are essential for accurate simulation and optimization, as detailed in Table 3.1. These parameters will be configurable through the user dashboard in the final implementation.

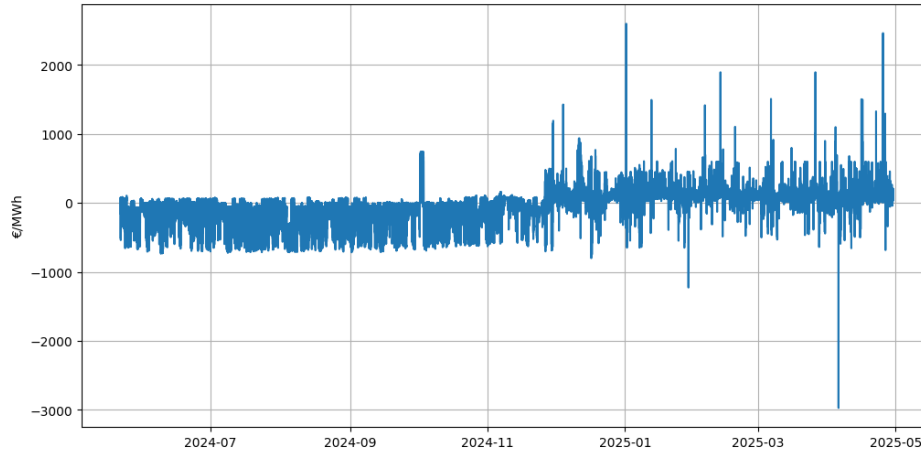


Figure 3.1: aFRR activation prices before and after the PICASSO market change

The model's operation is governed by several critical parameters. The initial State of Charge (SoC) establishes the battery's starting energy level. Power limits for both charging and discharging operations are defined as ranges rather than fixed values, enabling dynamic power flow control. This approach offers two key advantages: it helps extend battery lifespan by avoiding constant high-rate operations, and it provides the optimization model with flexibility to adjust power transfer rates based on market conditions and system constraints.

To ensure safe and efficient operation, the model implements operational SoC limits that prevent both overcharging and deep discharging scenarios, which could otherwise compromise battery health and safety.

Table 3.1: Battery parameters used in the model

Parameter	Value
Storage Capacity (C)	100 MWh
Initial State of Charge	40%
Charging Efficiency (η_c)	95%
Discharging Efficiency (η_d)	95%
Minimum Charging Power	0 MW
Maximum Charging Power	25 MW
Minimum Discharging Power	0 MW
Maximum Discharging Power	25 MW
Minimum SoC Allowed	20% of storage capacity
Maximum SoC Allowed	80% of storage capacity

3.3 Arbitrage Market

In the arbitrage market, Balance Responsible Parties (BRPs) engage in energy trading by purchasing electricity at lower prices and selling it at higher prices, similar to trading stocks but with energy. BRPs are entities responsible for maintaining the balance between electricity generation, consumption, and commercial transactions within their portfolios. They submit detailed schedules to the Transmission System Operator (TSO) outlining their planned energy injections and withdrawals. Any deviations from these schedules trigger imbalance settlements, where BRPs receive financial rewards or penalties based on the prevailing imbalance price [5].

BRPs can participate in the arbitrage market through two distinct periods: the day-ahead market and the real-time market. It is important to note that Frequency Containment Reserve (FCR) and Automatic Frequency Restoration Reserve (aFRR) mechanisms are not utilized for arbitrage trading, as they serve different purposes in grid stability.

The optimization model's objective for arbitrage is to maximize the energy storage system's net revenue by strategically charging the battery during low-price periods and discharging during high-price periods. This approach focuses solely on price differentials and does not consider grid frequency conditions. To evaluate revenue potential, two distinct models were developed and analyzed using historical data from both day-ahead and imbalance markets.

3.3.1 Implementation Architecture

The arbitrage optimization is implemented through two specialized computer programs that handle day-ahead pricing (DAP) and imbalance market scenarios. One program plans energy trades based on prices published a day in advance, while another responds to real-time price changes. Both implementations utilize the Pyomo optimization framework with similar mathematical formulations but different data sources and market-specific constraints.

The optimization model employs a linear programming approach, which aims to find the optimal solution of a linear function subject to linear constraints. In this context, it means finding the most profitable way to use the battery while staying within safety limits. The decision variables include charging power and discharging power (how much energy to store or release) at each time step. The model incorporates battery dynamics through state-of-charge tracking, efficiency considerations, and operational constraints. The implementation supports three distinct constraint scenarios to evaluate the impact of battery degradation limitations on profitability.

3.3.2 Mathematical Formulation

The core optimization problem is formulated as a linear program with the following structure:

Decision Variables

- $c_t \geq 0$ — charging power at time step t [MW], representing how much power to store
- $d_t \geq 0$ — discharging power at time step t [MW], representing how much power to release
- SoC_t — state of charge at time step t [MWh], representing how much energy is stored in the battery

Core Constraints

Note

The battery **cannot** charge and discharge **simultaneously** at any time step. The optimization model enforces this physical constraint by ensuring that either charging or discharging can occur, but not both at the same time.

State of Charge Dynamics The battery's energy balance is maintained through the following recursive constraint:

$$SoC_1 = \frac{SOC_{initial}}{100} \cdot C + \eta_c \cdot c_1 - \frac{d_1}{\eta_d} \quad (3.1)$$

$$SoC_t = SoC_{t-1} + \eta_c \cdot c_t - \frac{d_t}{\eta_d}, \quad \forall t > 1$$

These equations track how much energy is in the battery at each moment, accounting for energy losses when charging and discharging since batteries are not 100% efficient.

State of Charge Limits

$$SoC_{min} \leq SoC_t \leq SoC_{max}, \quad \forall t \in T \quad (3.2)$$

where $SoC_{min} = 0.2C$ and $SoC_{max} = 0.8C$ represent 20% and 80% of total battery capacity respectively.

The battery is never allowed to get completely empty (below 20%) or completely full (above 80%) to protect its lifespan and ensure safe operation.

Power Limits

$$0 \leq c_t \leq P_{charge,max}, \quad \forall t \in T \quad (3.3)$$

$$0 \leq d_t \leq P_{discharge,max}, \quad \forall t \in T \quad (3.4)$$

where P_{charge} = max charging power available [MW] and $P_{discharge}$ = max discharging power available [MW].

Cycle Life Constraints To mitigate battery degradation, the model incorporates constraints on energy throughput based on the number of allowable full cycles. These constraints are implemented across three optimization scenarios to evaluate the impact of different degradation management strategies on battery performance and profitability. The factor 2 in the constraint formulations accounts for one full cycle being composed of both a charging and discharging operation.

Scenario 1: Unconstrained Optimization

This scenario uses mathematical optimization without cycle constraints, maximizing profit based solely on battery parameters such as capacity, SoC limits, and charging/discharging power ratings. As it operates without degradation limits, it typically yields the highest profit potential but may result in accelerated battery aging.

Scenario 2: Monthly Cycle Constraint

This scenario introduces monthly degradation constraints by limiting the total energy throughput to $N_{monthly} = 45$ full cycles per month (equivalent to 1.5 cycles per day), derived from statistical analysis of recommended battery usage for health preservation [32]. The monthly constraint is reset at the beginning of each calendar month, meaning that the battery can utilize the full allowable cycle budget independently within each month without carrying over unused cycles from previous months.

Total energy throughput per month $\leq$ Maximum allowed energy throughput

$$\sum_{t \in \mathcal{T}_m} (c_t + d_t) \cdot \Delta t \leq 2 \cdot C \cdot N_{monthly}, \quad \forall m \in \text{Months} \quad (3.5)$$

where:

$\mathcal{T}_m = \{t : t \text{ belongs to month } m\}$

$N_{monthly} = 45$ cycles per month

C = Total battery capacity [MWh]

$\Delta t = 0.25$ hours (15-minute timestep)

c_t = Charging power at time t [MW]

d_t = Discharging power at time t [MW]

Scenario 3: Yearly Cycle Constraint

The final scenario imposes an annual limit of $N_{yearly} = 547.5$ full cycles per year (1.5×365 cycles). While this provides more flexibility in seasonal arbitrage and typically results in higher profits than the monthly-constrained case, it can lead to higher stress on the battery during peak price differential periods.

$$\sum_{t \in \mathcal{T}_y} (c_t + d_t) \cdot \Delta t \leq 2 \cdot C \cdot N_{yearly}, \quad \forall y \in \text{Years} \quad (3.6)$$

where $\mathcal{T}_y$ denote the time indices for each month and year respectively, C represents the total battery capacity [MWh], and Δt represent for the 15-minute timestep resolution.

These constraints limit how often the battery can be used each month or year to prevent it from wearing out too quickly, similar to limiting how many miles you drive to preserve your car's engine.

3.3.3 Mathematical Formulation

The primary objective of the optimization model is to maximize the net revenue generated through energy arbitrage. This is achieved by strategically charging and discharging the battery based on electricity market prices.

The optimization objective is mathematically expressed as:

$$\max \sum_{t \in T} \left(p_t \cdot d_t \cdot \eta_{dis} - p_t \cdot \frac{c_t}{\eta_{ch}} \right)$$

where:

- p_t — electricity price at time step t [€/MWh], the current market price
- d_t — discharging power at time t [MW], representing energy sales
- c_t — charging power at time t [MW], representing energy purchases
- η_{dis} — discharging efficiency, accounting for energy loss when selling
- η_{ch} — charging efficiency, accounting for energy loss when buying

This equation calculates profit by subtracting the cost of buying electricity from the revenue of selling electricity, while accounting for energy losses. The objective function accounts for both revenue generation from energy sales ($p_t \cdot d_t \cdot \eta_{dis}$) and energy purchase costs ($p_t \cdot \frac{c_t}{\eta_{ch}}$), while incorporating respective efficiency losses. The efficiency factors ensure that energy losses during charge and discharge cycles are properly accounted for in the economic optimization.

3.3.4 Market-Specific Implementations

Day-Ahead Market Model

The day-ahead market implementation plans battery operations based on electricity prices published one day in advance. The model utilizes hourly price signals from EPEX SPOT market data and processes CSV data containing timestamp and day-ahead price information.

The implementation includes specialized functions for result visualization, including state-of-charge heatmaps, seasonal profit analysis, and comparative scenario analysis. Results are exported in CSV format with detailed metrics including charging/discharging volumes, percentages, and profit calculations.

Imbalance Market Model

The imbalance market implementation responds to real-time electricity price changes that occur every 15 minutes based on grid imbalances. The model processes 15-minute resolution data from Elia's historical imbalance price dataset.

The imbalance model incorporates additional analysis features, including depth-of-discharge distribution analysis and comparative scenario evaluation across different constraint types.

3.3.5 Solution Methodology

The optimization models are solved using mixed-integer linear programming (MILP) solvers, a tool to find the minimum or maximum point of an objective function subjected to constraints that will be applied to determine the best battery operation strategy. The system includes automatic solver detection and fallback mechanisms, meaning if one program fails, the system automatically tries another one. The implementation supports multiple solvers including:

- GUROBI — Fastest commercial solver with advanced presolving and cutting plane techniques, typically 2-3x faster than open-source alternatives
- CPLEX — Comparable performance to GUROBI for large-scale problems, with strong parallel processing capabilities
- GLPK — Moderate performance open-source solver, generally 3-5x slower than commercial options
- CBC — Efficient open-source alternative with competitive performance for smaller problems, but scales less effectively than commercial solvers

3.4 Ancillary Market

In the ancillary market, Balancing Service Providers (BSPs) support keep the electricity grid stable by providing flexibility to the Transmission System Operator (TSO). Companies get paid both for being ready to support and for actually helping when needed. A BSP can be either a Balance Responsible Party (BRP) or a third party, and their primary role is to stabilize frequency control by injecting or absorbing power from the grid to maintain the nominal frequency of 50 Hz. BSPs participate in reserve capacity markets, including Frequency Containment Reserve (FCR) and Automatic Frequency Restoration Reserve (aFRR), by offering flexibility that can be activated upon request by the TSO. Compensation is provided for both reserved capacity and energy delivered during activations [5] for aFRR.

The ancillary market optimization encompasses four distinct service categories. Frequency Containment Reserve (FCR) provides an immediate and automatic response to frequency deviations, stabilizing the grid within seconds. Automatic Frequency Restoration Reserve (aFRR) is divided into two components: aFRR reservation, which refers to the pre-contracted availability of flexible resources, and aFRR activation, which involves the actual dispatch of those resources in

response to system operator signals. Finally, imbalance services are used to correct real-time discrepancies between supply and demand not covered by contracted reserves.

3.4.1 Unified Mathematical Framework

All ancillary service optimizations employ a consistent mathematical foundation while incorporating service-specific modifications. The unified framework employs Pyomo-based mixed-integer linear programming with specialized data preprocessing and multi-solver support.

Common Decision Variables and Constraints

1. Standard Decision Variables

All ancillary service models utilize the following core decision variables:

- $c_t, d_t \geq 0$ — charging and discharging power at time t [MW], determining energy flow direction and magnitude
- SoC_t — state of charge at time t [MWh], tracking cumulative battery energy level
- $z_t \in \{0, 1\}$ — binary charge/discharge operation indicator (1 = charging allowed, 0 = discharging allowed)

Additional service-specific variables are introduced as needed:

- C_{FCR}, P_{FCR} — FCR capacity and price bidding variables
- $x_i \in \{0, 1\}$ — aFRR reservation bid selection indicators
- $P_{4s}[t, s]$ — 4-second aFRR activation power signals
- α — activation probability scaling factors for risk adjustment

Note on Variable Notation

This methodology uses two distinct types of binary variables: (1) z_t for individual service charge/discharge operation control, and (2) $z_{t,m}$ for multi-market selection (introduced in the Multi-Market Framework section). These serve different mathematical purposes in their respective optimization contexts.

2. Universal Constraint Framework

The following constraints apply consistently across all ancillary service optimizations, eliminating the need for repetition in individual service descriptions:

State of Charge Dynamics:

$$SoC_1 = \frac{SOC_{initial}}{100} \cdot C + c_1 \cdot \eta_{ch} \cdot \Delta t - \frac{d_1 \cdot \Delta t}{\eta_{dis}} \quad (3.7)$$

$$SoC_t = SoC_{t-1} + c_t \cdot \eta_{ch} \cdot \Delta t - \frac{d_t \cdot \Delta t}{\eta_{dis}}, \quad \forall t > 1$$

Operational Bounds:

$$SoC_{min} \leq SoC_t \leq SoC_{max}, \quad \forall t \in T \quad (3.8)$$

$$0 \leq c_t \leq P_{ch,max}, \quad \forall t \in T \quad (3.9)$$

$$0 \leq d_t \leq P_{dis,max}, \quad \forall t \in T \quad (3.10)$$

where $SoC_{min} = 0.2C$, $SoC_{max} = 0.8C$, and $\Delta t = 15$ -minute resolution.

Cycle Life Constraints (when applicable):

$$\text{Monthly: } \sum_{t \in T_m} (c_t + d_t) \cdot \Delta t \leq 2 \cdot C \cdot N_{monthly}, \quad \forall m \quad (3.11)$$

$$\text{Yearly: } \sum_{t \in T_y} (c_t + d_t) \cdot \Delta t \leq 2 \cdot C \cdot N_{yearly}, \quad \forall y \quad (3.12)$$

Mutual Exclusivity (when required):

$$c_t \leq z_t \cdot P_{ch,max}, \quad \forall t \in T \quad (3.13)$$

$$d_t \leq (1 - z_t) \cdot P_{dis,max}, \quad \forall t \in T \quad (3.14)$$

These universal constraints ensure battery safety, operational feasibility, and degradation management across all ancillary services, while service-specific constraints address unique market requirements.

3.4.2 Service-Specific Formulations

FCR Optimization

FCR means offering to automatically support balance the grid for 4-hour periods by providing equal amounts of charging and discharging capability. The service operates on 4-hour blocks with symmetric capacity provision. The model introduces capacity bidding variables:

1. Additional Variables

- C_{FCR} — offered FCR capacity [MW], representing how much help we promise to provide
- P_{FCR} — bid price [€/MW], determining what we charge for our help
- $x_t \in [0, 1]$ — activation level at time t , showing how much of our capacity is actually used
- $b_t \in \{0, 1\}$ — bid selection indicator, indicating whether our bid was accepted

2. Objective and Key Constraints

$$\max \sum_{t \in T} C_{FCR} \cdot P_{FCR} \cdot b_t \cdot \Delta t - \lambda \cdot P_{FCR} \quad (3.15)$$

$$\text{s.t. } P_{FCR} - P_{market,t} \leq M \cdot (1 - b_t), \quad \forall t \in T \quad (3.16)$$

$$SoC_t = SoC_{t-1} - \Delta t \cdot \frac{C_{FCR} \cdot x_t}{\eta_{dis}} \quad (3.17)$$

This formulation maximizes revenue from capacity payments minus a penalty for bidding too high. Here, λ is a penalty coefficient that discourages excessively high bids, while M is a large constant (big-M) used in the constraint to ensure that when $b_t = 0$ (bid not accepted), the price constraint is effectively inactive. The constraint $P_{FCR} - P_{market,t} \leq M \cdot (1 - b_t)$ ensures that our bid price (P_{FCR}) must be lower than the market price ($P_{market,t}$) when our bid is accepted ($b_t = 1$). When $b_t = 0$, the large constant M makes this constraint non-binding.

aFRR Capacity Reservation

The aFRR capacity reservation optimization is crucial for maximizing revenue while managing battery resources effectively. This optimization is necessary because:

1. Market Dynamics: The aFRR market requires participants to commit capacity for both upward and downward regulation, with different price signals for each direction. The optimization helps identify the most profitable combination of capacity commitments.
2. Resource Constraints: The battery has limited capacity (20 MW) that must be optimally allocated between upward and downward regulation. The optimization ensures we don't overcommit our resources.
3. Historical Price Patterns: By analyzing past successful bids, we can identify patterns in market prices and capacity requirements that lead to the highest revenue potential.
4. Bid Selection Probability: The optimization considers the likelihood of bid acceptance by analyzing historical selection patterns. This helps us avoid submitting bids that are unlikely to be selected, even if they offer high potential revenue.

The optimization is formulated as:

$$\max \sum_{i \in B} x_i \cdot [C_{up,i} \cdot P_{up,i} + C_{down,i} \cdot P_{down,i}] \quad (3.18)$$

$$\text{s.t.} \quad \sum_{i \in B} x_i = 1 \quad (3.19)$$

$$\sum_{i \in B} x_i \cdot C_{up/down,i} \leq C_{max} = 20 \text{ MW} \quad (3.20)$$

where:

- $x_i \in \{0, 1\}$ represents the binary decision variable for selecting bid pattern i , where 1 indicates selection and 0 indicates non-selection
- $C_{up,i}$ and $C_{down,i}$ are the upward and downward capacity commitments
- $P_{up,i}$ and $P_{down,i}$ are the corresponding prices
- The constraints ensure we select exactly one bid pattern while respecting our 20 MW capacity limit

This optimization helps us make informed decisions about capacity reservation by identifying the most profitable historical bid patterns that align with our battery's capabilities and market conditions, while maximizing the probability of bid acceptance.

aFRR Activation Service

The aFRR activation service provides real-time energy delivery when the transmission system operator calls upon reserved aFRR capacity to address frequency deviations. The service incorporates high-frequency modeling to capture the dynamics of actual grid response requirements.

1. High-Frequency Signal Modeling

The implementation models aFRR activation at 4-second resolution to accurately represent the real-time nature of frequency response services. Each 15-minute optimization period contains 225 4-second intervals with stochastic activation signals generated as:

$$P_{4s}[t, s] \sim \mathcal{N}(0, \sigma = 10 \text{ MW}), \quad s \in \{0, 1, \dots, 224\} \quad (3.21)$$

where t represents the 15-minute period and s indexes the 4-second intervals within each period. This stochastic modeling approach reflects the uncertainty and variability in actual grid frequency response requirements based on historical activation patterns from ENTSO-E CBMP data.

2. System Imbalance-Based Activation Logic

The activation logic responds directly to real-time system imbalance conditions, ensuring grid stability through appropriate battery response:

$$\text{If } \text{imbalance}_t < 0 : \quad P_{\text{discharge},t} \leq \min(|\text{imbalance}_t|, P_{\text{discharge},\max}) \quad (3.22)$$

$$P_{\text{charge},t} = 0 \quad (3.23)$$

$$\text{If } \text{imbalance}_t > 0 : \quad P_{\text{charge},t} \leq \min(\text{imbalance}_t, P_{\text{charge},\max}) \quad (3.24)$$

$$P_{\text{discharge},t} = 0 \quad (3.25)$$

$$\text{If } \text{imbalance}_t = 0 : \quad P_{\text{charge},t} = P_{\text{discharge},t} = 0 \quad (3.26)$$

This conditional logic ensures that the battery provides upward regulation (discharging) when the grid experiences a power deficit and downward regulation (charging) when there is excess power, with activation limited by both the magnitude of imbalance and battery power constraints.

3. Revenue Structure

The aFRR activation revenue differentiates between upward and downward regulation with market-specific pricing:

$$R_t^{\text{aFRR}} = P_{\text{up},t} \cdot P_{\text{discharge},t} \cdot \eta_{\text{dis}} - P_{\text{down},t} \cdot \frac{P_{\text{charge},t}}{\eta_{\text{ch}}} \quad (3.27)$$

where $P_{\text{up},t}$ and $P_{\text{down},t}$ represent the upward and downward aFRR activation prices, respectively, reflecting the different values of positive and negative frequency regulation services.

Imbalance Ancillary Service

The imbalance ancillary service provides secondary balancing support during grid imbalances, operating as a complementary service to primary imbalance arbitrage with reduced activation certainty. This service leverages the same real-time imbalance price signals but accounts for lower activation probability due to its auxiliary role in grid balancing.

1. Risk-Adjusted Revenue Model

The imbalance ancillary service employs a probability-weighted revenue calculation to reflect the reduced likelihood of activation compared to primary balancing services:

$$R_t^{\text{imbalance_ancillary}} = p_t \cdot \left(P_{\text{discharge},t} \cdot \eta_{\text{dis}} - \frac{P_{\text{charge},t}}{\eta_{\text{ch}}} \right) \cdot \alpha \quad (3.28)$$

where p_t represents the real-time imbalance price and α represents the activation probability factor. This conservative factor reflects that the imbalance ancillary service operates

as a secondary backup to primary imbalance mechanisms, meaning that even when the battery is committed to providing this service, there is only a limited likelihood that the TSO will actually call upon it for grid support at any given time period. This probability weighting accounts for the TSO's multiple balancing options and the unpredictable nature of grid imbalances requiring secondary support.

2. Operational Constraints

The service follows the same conditional response logic as aFRR activation but with additional risk considerations:

$$\text{Activation constraint: } P_{total,t} \leq P_{available,t} \cdot \alpha \quad (3.29)$$

$$\text{Response capability: } P_{charge,t} + P_{discharge,t} \leq P_{max} \cdot z_{t,imbalance_ancillary} \quad (3.30)$$

where $P_{available,t}$ represents the available battery capacity and $z_{t,imbalance_ancillary}$ is the binary variable for imbalance ancillary service activation (1 = service active, 0 = service inactive).

3.4.3 Implementation Architecture and Code References

The ancillary services optimization is implemented through four specialized Python modules, each handling distinct market characteristics while sharing common infrastructure components. Table 3.2 provides the mapping between market services and their corresponding code implementations.

Table 3.2: Implementation modules for ancillary services

Service	Key Features
FCR	McCormick constraints, 4-hour blocks
aFRR Reservation	Binary bid selection, historical data
aFRR Activation	4-second signals, CBMP integration
Imbalance Ancillary	Risk-adjusted revenue, conditional logic

Market-Specific Data Processing

Each ancillary service module implements specialized data preprocessing routines:

- **FCR:** Regelleistung data filtering, 4-hour block aggregation, deficit/surplus calculation
- **aFRR Reservation:** Capacity bid parsing, award percentage analysis, delivery period handling
- **aFRR Activation:** CBMP data alignment, 4-second signal generation, imbalance correlation
- **Imbalance Ancillary:** Real-time price filtering, activation probability modeling, risk adjustment

3.4.4 Market Coordination

The modular architecture enables sequential market participation with cross-market constraint handling. The system coordinates between different markets to ensure that capacity reserved in one market remains available for activation while supporting revenue diversification across multiple ancillary service categories. This prevents double-booking of battery capacity while maximizing revenue from multiple services.

3.5 Combination of arbitrage and ancillary market

The ultimate goal of Energy Storage System (ESS) optimization is to participate simultaneously in multiple electricity markets to maximize total revenue while respecting operational constraints. Rather than optimizing each market separately, the comprehensive approach integrates arbitrage and ancillary services into a unified optimization framework. This means the battery system can choose the most profitable market at each moment while ensuring it doesn't double-book its capacity across multiple services.

The multi-market optimization addresses a fundamental challenge in electricity markets: a battery has limited capacity and power that can only be used in one way at any given time. When multiple markets offer different revenue opportunities simultaneously, the system must decide which market provides the highest value while maintaining grid stability commitments and battery health preservation.

3.5.1 Multi-Market Selection Framework

The integrated optimization model employs a market selection approach using binary decision variables to coordinate participation across six distinct market segments. At each 15-minute time period, the optimization system chooses exactly one market from the available options, ensuring exclusive allocation of battery capacity while maximizing total revenue across the entire planning horizon.

The six available markets in the integrated framework include:

- **Day-Ahead Market (DAM)** — energy arbitrage based on scheduled day-ahead prices published by EPEX SPOT
- **Imbalance Arbitrage** — real-time energy trading responding to 15-minute imbalance price signals from Elia
- **Frequency Containment Reserve (FCR)** — symmetric capacity provision for automatic frequency stabilization in 4-hour blocks
- **aFRR Capacity Reservation** — upward and downward flexibility reservation for secondary frequency control
- **aFRR Activation** — energy delivery during actual aFRR reserve activations based on grid needs
- **Imbalance Ancillary** — balancing service provision during real-time grid imbalances with reduced activation probability

3.5.2 Mathematical Formulation

Unified Objective Function

The multi-market optimization maximizes total revenue across all markets and time periods:

$$\max \sum_{t \in T} \sum_{m \in M} R_{t,m} \quad (3.31)$$

where $R_{t,m}$ represents the appropriate revenue expression for market m during period t , as defined by the market-specific formulations above.

Market Selection Variables

The core innovation of the multi-market approach lies in the binary market selection variables:

$$z_{t,m} \in \{0, 1\}, \quad \forall t \in T, \forall m \in M \quad (3.32)$$

where $z_{t,m} = 1$ indicates that market m is selected during time period t , and $M = \{\text{DAP, Imbalance Arbitrage, FCR, aFRR Reservation, aFRR Activation, Imbalance Ancillary}\}$ represents the set of available markets.

Market Exclusivity Constraint

To prevent double-booking of battery capacity and ensure realistic market participation, the model enforces exclusive market selection:

$$\sum_{m \in M} z_{t,m} = 1, \quad \forall t \in T \quad (3.33)$$

This constraint ensures that exactly one market is selected during each time period, meaning the battery cannot simultaneously participate in multiple markets that would require the same capacity resources.

Auxiliary Power Variables and Linearization

To handle the market selection logic mathematically, the model introduces auxiliary power variables that link charging and discharging decisions to specific markets:

$$P_{\text{charge},t,m} \geq 0, \quad \forall t \in T, \forall m \in M \quad (3.34)$$

$$P_{\text{discharge},t,m} \geq 0, \quad \forall t \in T, \forall m \in M \quad (3.35)$$

These auxiliary variables are constrained by the market selection variables using Big-M constraints, which is a standard mathematical technique for handling logical conditions in optimization:

$$P_{\text{charge},t,m} \leq P_{\text{charge},\max} \cdot z_{t,m}, \quad \forall t \in T, \forall m \in M \quad (3.36)$$

$$P_{\text{discharge},t,m} \leq P_{\text{discharge},\max} \cdot z_{t,m}, \quad \forall t \in T, \forall m \in M \quad (3.37)$$

The total charging and discharging power across all markets must equal the actual battery operation:

$$P_{charge,t} = \sum_{m \in M} P_{charge,t,m}, \quad \forall t \in T \quad (3.38)$$

$$P_{discharge,t} = \sum_{m \in M} P_{discharge,t,m}, \quad \forall t \in T \quad (3.39)$$

Market-Specific Revenue Expressions

Each market has distinct pricing mechanisms and revenue structures that are mathematically represented through specialized revenue expressions:

Energy Arbitrage Markets (DAP and Imbalance):

$$R_{t,m}^{arbitrage} = p_{t,m} \cdot \left(P_{discharge,t,m} \cdot \eta_{dis} - \frac{P_{charge,t,m}}{\eta_{ch}} \right) \quad (3.40)$$

These markets generate revenue by selling electricity at high prices and purchasing at low prices, accounting for battery efficiency losses during charge and discharge cycles.

Capacity Markets (FCR and aFRR Reservation):

$$R_{t,m}^{capacity} = p_{t,m} \cdot (P_{charge,t,m} + P_{discharge,t,m}) \cdot \Delta t \quad (3.41)$$

Capacity markets compensate for the availability to provide grid services, paying for reserved power capability regardless of actual energy delivery. The timestep factor $\Delta t = 15$ -minute intervals.

Activation Markets (aFRR Activation and Imbalance Ancillary):

$$R_{t,m}^{activation} = p_{t,m} \cdot \left(P_{discharge,t,m} \cdot \eta_{dis} - \frac{P_{charge,t,m}}{\eta_{ch}} \right) \cdot \alpha_m \quad (3.42)$$

where α_m represents the activation probability factor for market m . For activation-based ancillary services (aFRR Activation and Imbalance Ancillary), α_m reflects the realistic expectation that the TSO will only call upon these services in a limited fraction of the time periods when they are available. This conservative modeling accounts for several factors:

- the TSO has multiple reserve providers and may not need all available resources
- actual grid frequency deviations requiring ancillary service activation are unpredictable and relatively infrequent
- the battery may be held in reserve but not activated due to sufficient response from other providers.

This probability weighting ensures revenue projections remain realistic rather than overly optimistic.

3.5.3 Market Coordination Constraints and Cross-Market Logic

The multi-market optimization requires sophisticated coordination mechanisms to ensure realistic market participation while maximizing revenue opportunities. The coordination framework addresses temporal dependencies, capacity allocation conflicts, and operational feasibility across different market segments.

Temporal Market Dependencies

Several markets exhibit inherent temporal relationships that must be respected in the optimization model:

aFRR Service Coordination The aFRR activation service can only be utilized when corresponding capacity has been previously reserved, reflecting the two-stage nature of aFRR market participation:

$$z_{t,\text{aFRR Activation}} \leq z_{t,\text{aFRR Reservation}}, \quad \forall t \in T \quad (3.43)$$

This constraint ensures energy delivery through aFRR activation only occurs when the corresponding capacity reservation was established in the same time period, maintaining consistency with actual TSO operational procedures.

FCR Block Continuity FCR services operate in 4-hour delivery blocks, requiring coordination across multiple 15-minute optimization periods:

$$\sum_{j=0}^{15} z_{t+j,\text{FCR}} \geq 16 \cdot z_{t,\text{FCR}}, \quad \forall t \in T_{4h_start} \quad (3.44)$$

where j is an index variable ranging from 0 to 15 that serves as an offset from the starting time period t , allowing the constraint to reference 16 consecutive 15-minute periods ($t, t+1, t+2, \dots, t+15$) that comprise the 4-hour FCR delivery block. T_{4h_start} represents the starting periods of 4-hour blocks, ensuring that FCR commitment is maintained for the entire delivery period once selected.

Capacity Conflict Resolution

The coordination framework prevents simultaneous allocation of limited battery capacity to conflicting market opportunities:

Power Allocation Consistency The total power allocation across all selected markets cannot exceed physical battery limitations:

$$\sum_{m \in M} P_{\text{charge},t,m} \leq P_{\text{charge,max}}, \quad \forall t \in T \quad (3.45)$$

$$\sum_{m \in M} P_{\text{discharge},t,m} \leq P_{\text{discharge,max}}, \quad \forall t \in T \quad (3.46)$$

Energy State Coordination All markets must operate from the same battery state of charge, ensuring consistent energy tracking regardless of market selection:

$$SoC_t = SoC_{t-1} + \Delta t \cdot \left(\eta_{ch} \cdot \sum_{m \in M} P_{charge,t,m} - \frac{\sum_{m \in M} P_{discharge,t,m}}{\eta_{dis}} \right) \quad (3.47)$$

Battery State of Charge Consistency

The SoC evolution remains consistent across all markets using the same fundamental dynamics as individual market models:

$$SoC_t = SoC_{t-1} + \Delta t \cdot \left(\eta_{ch} \cdot P_{charge,t} - \frac{P_{discharge,t}}{\eta_{dis}} \right), \quad \forall t > 1 \quad (3.48)$$

The same SoC limits and power constraints apply regardless of which market is selected, ensuring battery safety and operational feasibility across all market participation modes.

3.5.4 Implementation Architecture

Data Integration and Preprocessing

The multi-market implementation requires harmonization of different data sources with varying temporal resolutions and market-specific characteristics:

- **Temporal Alignment** — All market data is aligned to a common 15-minute resolution grid to enable synchronized optimization across different time periods
- **Price Normalization** — Market prices are converted to consistent units (€/MWh for energy, €/MW/h for capacity) with appropriate scaling factors
- **Missing Data Handling** — Placeholder data generation for markets without complete historical datasets, using representative average prices based on market analysis
- **Index Synchronization** — All market datasets are aligned to the same datetime index to ensure proper temporal matching during optimization

Optimization Solution Strategy

The multi-market model employs advanced mixed-integer linear programming (MILP) techniques to handle the binary market selection variables efficiently.

- **Solver Selection** — Automatic detection and fallback mechanisms supporting commercial solvers (GUROBI, CPLEX) and open-source alternatives (GLPK, CBC)
- **Linearization Techniques** — Big-M constraints and auxiliary variables to convert logical market selection decisions into linear mathematical expressions
- **Performance Optimization** — Time limits and optimality gaps to balance solution quality with computational efficiency
- **Solution Validation** — Post-processing checks to ensure market selection exclusivity and feasibility of the optimal solution

3.5.5 Scenario Analysis Framework

The multi-market optimization supports the same three constraint scenarios as individual market models, enabling comparative analysis of degradation impact across integrated market participation:

1. **Unconstrained Multi-Market** — Maximum theoretical revenue potential across all markets without cycle limitations
2. **Monthly Cycle Constraints** — Distributed cycle limits that restrict total battery usage across all selected markets to preserve long-term battery health
3. **Yearly Cycle Constraints** — Annual cycle limits providing seasonal flexibility while maintaining battery health over longer planning horizons

Each scenario generates comprehensive results including market selection patterns, revenue attribution by market type, temporal distribution of operations, and comparative analysis against single-market optimization strategies.

3.5.6 Revenue Attribution and Market Selection Analysis

The multi-market optimization provides detailed analytics on market selection patterns and revenue distribution:

Market Selection Frequency The optimization reveals which markets are most frequently selected under different constraint scenarios, providing insights into the relative attractiveness of different revenue streams.

Revenue Share Analysis Detailed breakdown of total revenue by market type shows the contribution of each market segment to overall profitability, helping identify the most valuable market opportunities.

Temporal Market Patterns Analysis of market selection over time reveals seasonal preferences, daily patterns, and the impact of price volatility on optimal market choice.

This comprehensive approach enables BESS operators to understand not just total profitability, but also the strategic value of different market segments and the optimal balance between arbitrage and ancillary service participation. The framework provides essential insights for investment decisions, operational strategies, and regulatory participation in evolving electricity markets.

3.5.7 Methodology Summary and Integration

The complete methodology encompasses three complementary optimization approaches: individual market optimization, ancillary service coordination, and integrated multi-market optimization. Each approach serves distinct analytical purposes while building upon shared mathematical foundations.

Methodological Hierarchy

1. **Individual Market Analysis** Establishes baseline performance metrics and market-specific optimization strategies for DAP arbitrage, imbalance arbitrage, FCR, aFRR reservation, aFRR activation, and imbalance ancillary services
2. **Ancillary Service Integration** Coordinates FCR and aFRR services with cross-temporal constraints and capacity management while maintaining individual service optimality
3. **Multi-Market Optimization** Integrates all six market segments with binary market selection, ensuring exclusive capacity allocation and revenue maximization across the complete market spectrum

Key Methodological Innovations

The developed framework introduces several novel approaches to BESS market participation optimization:

- **High-Resolution Temporal Modeling:** 4-second aFRR activation signals aggregated to 15-minute optimization periods
- **Risk-Adjusted Revenue Calculation:** Probability-weighted returns for ancillary services with uncertain activation
- **Cross-Market Constraint Coordination:** Logical dependencies between aFRR reservation and activation with FCR block continuity
- **Unified Degradation Management:** Consistent cycle life constraints across all market participation modes
- **Dynamic Market Selection:** Binary optimization variables enabling real-time market switching based on economic opportunities

The integrated methodology provides a comprehensive foundation for understanding BESS economic potential across Belgian electricity markets, enabling informed investment decisions and optimal operational strategies in complex multi-market environment.

Chapter 4

Consideration and decision regarding alternative solutions

This chapter discusses the alternative approaches considered during the development of the optimization model, the rationale behind key design decisions, and the trade-offs that influenced the final methodology. The considerations presented here provide transparency regarding the research choices and acknowledge limitations while justifying the selected approach.

4.1 Optimization Methodology Selection

The fundamental design decision involved choosing between single-market and multi-market optimization approaches. A single-market approach would develop separate optimization models for each market, offering simpler model formulation and easier validation. However, this approach was rejected due to suboptimal resource allocation and the inability to capture market interactions, which would result in significant revenue losses from missed arbitrage opportunities between markets.

The selected multi-market approach simultaneously optimizes across all available markets, capturing market synergies and maximizing overall revenue while providing a realistic representation of actual market participation strategies. Although this increases model complexity and computational requirements, it better represents real-world operational conditions where storage operators must dynamically allocate capacity across multiple revenue streams.

Regarding the optimization technique, three main approaches were evaluated. Linear Programming (LP) offers guaranteed global optimum and fast computation but cannot accurately handle non-linear battery degradation or efficiency curves. Non-Linear Programming (NLP) provides more accurate representation of battery characteristics but offers no guarantee of global optimum and suffers from computational complexity. Mixed-Integer Linear Programming (MILP) was selected as the optimal balance, handling discrete decisions such as market participation while maintaining good computational performance and providing optimal solutions within the linearized framework.

4.2 Technology and Market Considerations

The study focuses on any type of battery technology based on its market dominance in grid-scale applications, well-documented degradation characteristics, and suitability for frequent cycling applications. Alternative technologies such as flow batteries, compressed air energy storage, and

pumped hydro could be also implemented in the model.

Market selection was based on several criteria including sufficient trading volume for meaningful participation, historical price volatility enabling arbitrage opportunities, regulatory accessibility for private operators, and data availability for model validation. The technical requirements of each market were also considered, particularly response time requirements where FCR requires within 30-second response and aFRR requires 5-minute response, along with minimum participation thresholds and certification requirements.

The optimization model considers multiple battery sizes ranging from 1 MW to 25 MW to analyze economies of scale effects, identify optimal sizing for different market conditions, and assess the impact on revenue per MW installed while considering practical deployment constraints.

4.3 Data and Modeling Framework

A 15-minute time resolution was selected to align with Belgian imbalance settlement periods while providing sufficient granularity for most market mechanisms. This resolution offers manageable computational requirements and represents the standard resolution for European markets. Alternative resolutions such as 5-minute intervals would be more accurate but computationally intensive, while 1-hour intervals would be insufficient for fast response services.

For battery degradation modeling, a simplified linear degradation approach was selected based on computational efficiency while capturing primary degradation effects. The parameters are based on manufacturer specifications and literature, though this approach does not capture temperature dependencies or depth-of-discharge impacts, which are considered for future work.

Economic considerations relevant to battery storage projects include capital expenditures such as power conversion systems, installation, and commissioning as well as operational expenses like maintenance (typically 2–3% of CAPEX annually), grid connection charges, insurance, and regulatory compliance costs. While these factors are critical for assessing long-term viability, they are not included in the current optimization model. Instead, the model focuses solely on market revenues. Revenue streams are defined per market: arbitrage is based on energy price differentials adjusted for efficiency losses; FCR includes both capacity and activation payments; aFRR includes reservation and activation payments; and the imbalance mechanism reflects real-time system needs. Incorporating the full spectrum of economic costs remains part of future work aimed at improving techno-economic realism.

4.4 Model Limitations and Validation

Several important limitations are acknowledged in the model formulation. The price-taker assumption implies that battery operation does not influence market prices, which is reasonable for smaller installations but may not hold for very large deployments. The historical analysis assumes perfect information, eliminating uncertainty effects that would be present in real-time operations. Grid constraints and transmission limitations are not explicitly modeled, and geographic arbitrage opportunities are not considered as the model focuses on a single location.

Regulatory assumptions include stability of current market rules throughout the analysis period, no regulatory barriers to market participation, constant taxation and subsidy frameworks, and approved grid connections. These assumptions may not hold in practice, particularly given the evolving nature of energy markets and regulations.

The model validation strategy employs historical backtesting with out-of-sample testing on 2024 data, comparison with actual market participant results where available, and sensitivity analysis

on key parameters. Time-series cross-validation with expanding windows is used to assess performance across different market conditions, with separate validation for each market mechanism using performance metrics including revenue, utilization, and risk measures.

4.5 Implementation and Scalability

Practical deployment considerations include real-time data feed requirements, automated bidding system development, grid connection protocols, and backup systems. Operational requirements encompass 24/7 monitoring capabilities, maintenance scheduling around market commitments, and staff training requirements.

The optimization framework is designed for scalability to larger battery installations, adaptation to additional market mechanisms, incorporation of multiple battery sites, and extension to other European markets with similar structures. These design decisions prioritize practical applicability over theoretical perfection, computational efficiency enabling real-time implementation, market realism reflecting actual operational constraints, and transparency in assumptions and limitations.

The considerations outlined ensure that the optimization model provides actionable insights for energy storage investors and operators while acknowledging the complexities and uncertainties inherent in multi-market participation strategies. Future work should address more sophisticated degradation modeling, uncertainty quantification, and extension to additional market mechanisms as they become available.

Chapter 5

Results and Discussion

This section presents the comprehensive results obtained from the multi-market optimization strategy for battery energy storage systems in the Belgian electricity market. The analysis encompasses three key areas:

- Technical performance metrics including State of Charge (SoC) evolution.
- Economic performance through revenue analysis.
- Operational behavior across different market scenarios.

5.1 aFRR Reservation Optimization Results

The aFRR capacity reservation optimization demonstrates the complexity of bidding strategies in ancillary service markets. The optimization algorithm evaluates historical bidding patterns to identify the most profitable capacity combinations while ensuring bid acceptance probability. Analysis of a representative day (January 20, 2024 in figure [A.1](#)) shows significant variation in optimal capacity allocation between upward and downward regulation services throughout the day.

The optimization results reveal that successful bidding strategies require dynamic adjustment of capacity offerings based on market conditions. During peak demand periods, the system prioritizes upward regulation capacity (typically 15-20 MW), while off-peak periods show preference for balanced capacity allocation (8-12 MW each direction).

The revenue contribution from aFRR reservation services varies significantly with market constraints, ranging from €7.7M in unconstrained scenarios to €0.9M under yearly cycle constraints, demonstrating the trade-off between aggressive market participation and battery degradation management.

5.2 Revenue Performance Analysis

The economic performance evaluation constitutes the primary objective function of the optimization strategy. The revenue comparison across different scenarios is presented in Table [5.1](#), which demonstrates the trade-offs between profitability and operational constraints.

Table 5.1: Revenue performance comparison across different constraint scenarios, highlighting the economic impact of cycle life limitations on battery profitability

Scenario	Total Revenue (€)	Annual Cycles	Total charge [MWh]	Total discharge [MWh]
Unconstrained	121,646,027	2519.5	251950.77	204198.63
Monthly Constraint	46,445,377	540	57510.49	46702.00
Yearly Constraint	39,923,743	547.5	36500.00	29683.50

5.2.1 Total Revenue Analysis

The simulation results in table 5.1 demonstrate significant variations in total revenue generation across the three operational scenarios:

- **Unconstrained Scenario:** Achieved a total annual revenue of approximately €121,646,027, representing the theoretical maximum profitability under ideal conditions without degradation considerations.
- **Monthly Constraint Scenario:** Generated a total annual revenue of €46,445,377, representing a 63.6% reduction compared to the unconstrained scenario with a total of 540 cycles in one year. This reduction reflects the cost of implementing conservative degradation management strategies.
- **Yearly Constraint Scenario:** Produced a total annual revenue of €39,923,743, achieving 32.9% of the unconstrained scenario's performance while maintaining degradation control through annual cycle limitations.

5.2.2 Revenue Distribution Over Time

The temporal revenue distribution analysis reveals important insights about market dynamics and optimal participation strategies. The profit evolution subplots (Figure 5.1) illustrate how revenues accumulate across different time periods and market conditions.

Table 5.2: Market Share Distribution by Scenario over time (%)

Scenario	DAP	Imbalance Arbitrage	FCR	aFRR Reservation	aFRR Activation	Imbalance Ancillary
No Constraints	31.9%	14.7%	21.6%	31.8%	0.0%	0.0%
Monthly Constraints	30.2%	13.6%	9.4%	44.7%	0.0%	2.1%
Yearly Constraints	14.8%	6.7%	4.3%	72.6%	0.0%	1.7%

The revenue analysis demonstrates significant differences between market participation time allocation and actual revenue generation. As shown in Table 5.2, while aFRR Reservation commands the highest time allocation under constrained scenarios (44.7% monthly, 72.6% yearly), Table 5.4 reveals that DAP arbitrage dominates actual revenue generation across all scenarios (67.7-72.3% of total revenue).

5.2.3 Market-Specific Revenue Contributions

The market selection analysis reveals a clear hierarchy in revenue generation effectiveness. As detailed in Table 5.3, DAP arbitrage consistently provides the largest revenue contribution, ranging from €28.9M to €87.4M depending on constraint scenarios. Imbalance arbitrage serves as the second-largest revenue source, contributing €9.8M to €21.5M across scenarios. Ancillary services (FCR and aFRR Reservation) provide supplementary revenue streams but with significantly lower absolute contributions, ranging from €0.3M to €7.7M combined. The FCR market

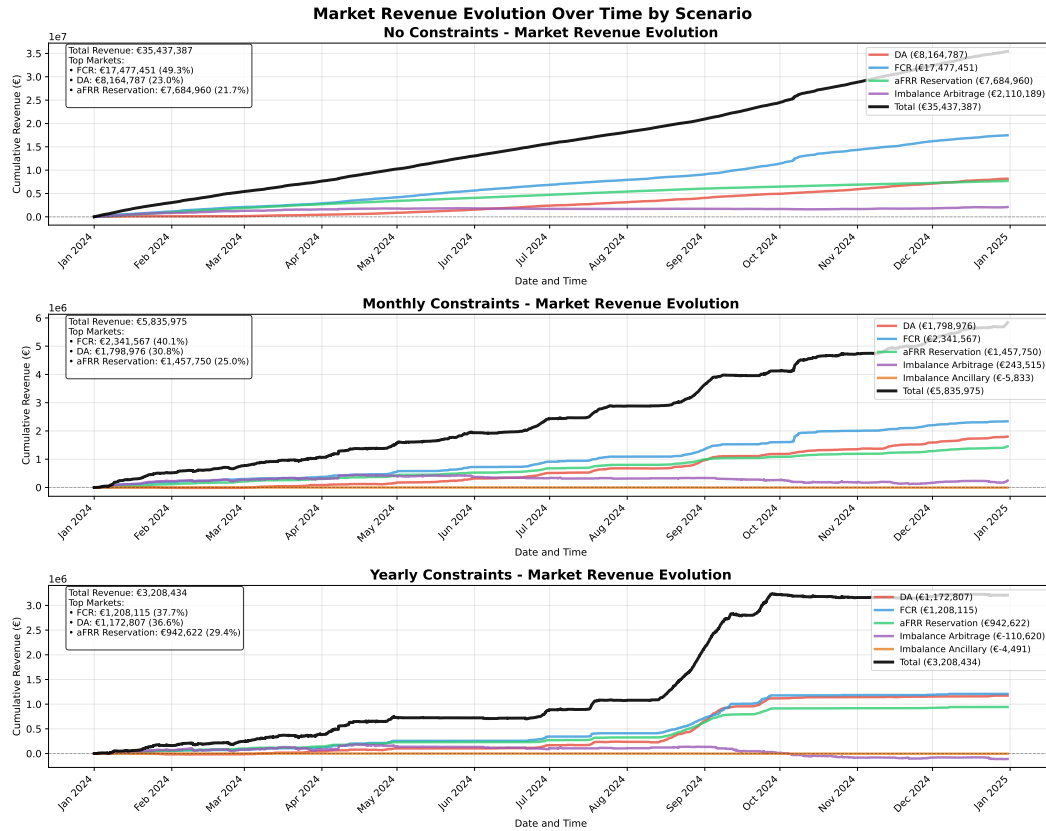


Figure 5.1: Detailed profit evolution analysis showing cumulative revenue development, daily variation patterns, and seasonal trends across the optimization period

optimization strategies and their revenue impact are detailed in the comprehensive analysis (Appendix A.5) and system comparison (Appendix A.6).

Table 5.3: Absolute Revenue by Market and Scenario (€)

Scenario	DAP	Imbalance Arbitrage	FCR	aFRR Reservation	aFRR Activation	Imbalance Ancillary
No Constraints	€87,395,836	€21,515,146	€5,005,084	€7,684,960	€0	€0
Monthly Constraints	€31,432,618	€12,898,730	€657,345	€1,457,750	€0	€-1,066
Yearly Constraints	€28,865,735	€9,780,639	€336,298	€942,622	€0	€-1,701

Table 5.4: Revenue Share Distribution by Scenario (%)

Scenario	DAP	Imbalance Arbitrage	FCR	aFRR Reservation	aFRR Activation	Imbalance Ancillary
No Constraints	71.8%	17.7%	4.2%	6.3%	0.0%	0.0%
Monthly Constraints	67.7%	27.8%	1.4%	3.1%	0.0%	0.0%
Yearly Constraints	72.3%	24.5%	0.8%	2.4%	0.0%	0.0%

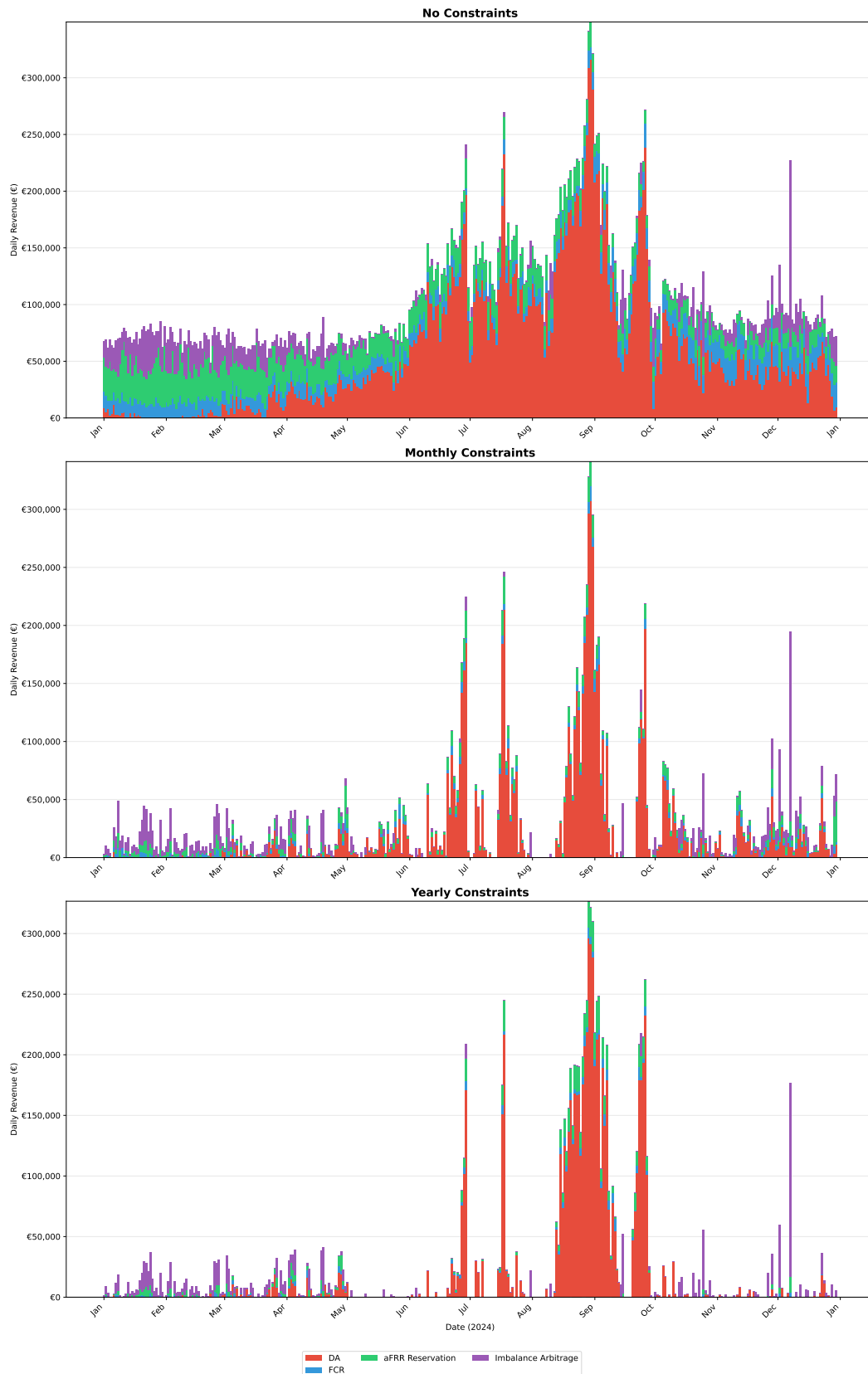


Figure 5.2: Absolute revenue contribution analysis across different market segments, showing the total monetary value generated by each market type throughout the optimization period

The absolute revenue analysis (Figure 5.2) provides a detailed breakdown of the monetary contributions from each market segment. The visualization reveals that day-ahead market arbitrage

generates the highest absolute revenue, followed by imbalance arbitrage and FCR services. This distribution highlights the importance of maintaining a diversified market participation strategy to maximize total revenue potential. The analysis also shows significant variations in revenue contributions across different time periods, reflecting the dynamic nature of electricity markets and the optimization algorithm's ability to adapt to changing market conditions.

5.3 State of Charge Analysis

The State of Charge (SoC) evolution represents a critical operational parameter for battery energy storage systems, as it directly influences both the technical feasibility and economic viability of market participation strategies.

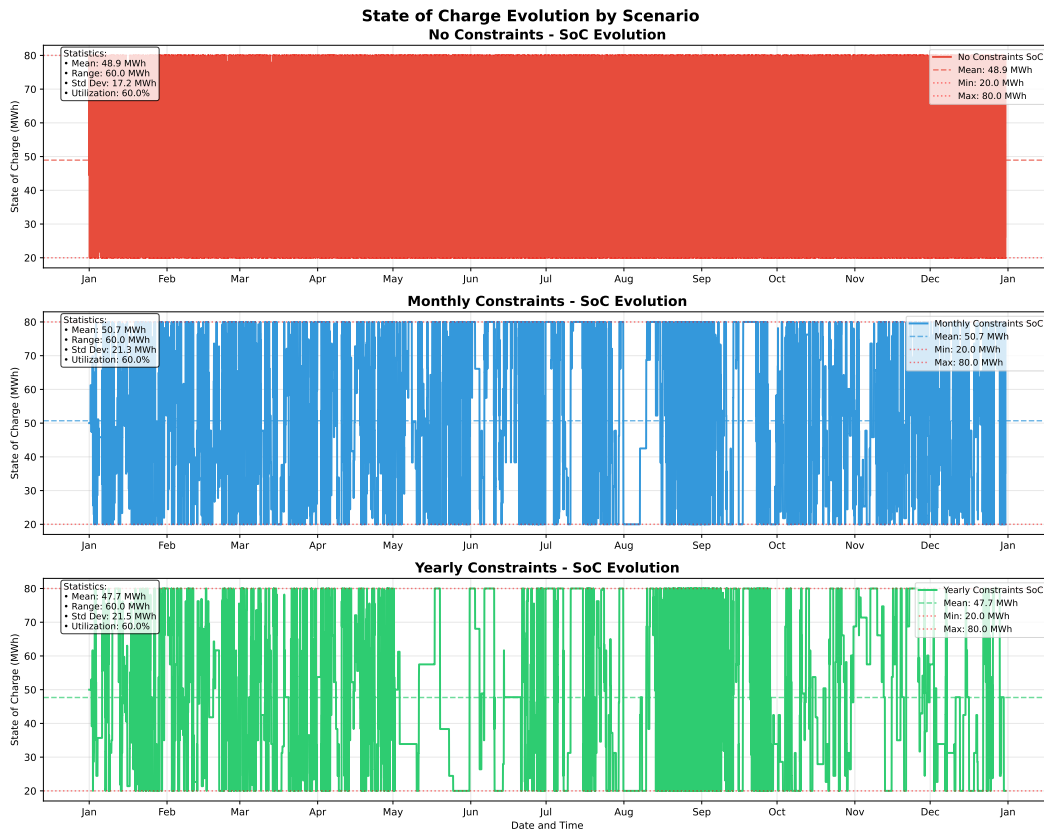


Figure 5.3: Comprehensive State of Charge analysis showing distribution patterns, utilization efficiency, and operational boundaries throughout the optimization period

The analysis reveals in figure 5.3 distinct operational patterns across the three constraint scenarios. The daily cycles comparison (Appendix A.3) illustrates how constraint limitations fundamentally alter battery utilization strategies.

1. In the unconstrained scenario, the battery demonstrates aggressive cycling behavior with frequent transitions between charging and discharging states, resulting in an average SoC utilization of approximately 68.4% of the available capacity window (20%-80%). This aggressive cycling pattern maximizes revenue potential but may accelerate battery degradation.
2. The monthly constraint scenario shows more conservative SoC management compared to unconstrained scenario. The system maintains more stable SoC levels during periods of

limited arbitrage opportunities, preserving cycle life for high-value trading periods. This strategic approach balances profitability with battery longevity considerations.

3. The yearly constraint scenario exhibits intermediate behaviour. The flexibility to distribute cycles across the entire year enables more efficient exploitation of seasonal price variations while maintaining degradation control, as demonstrated in the seasonal profit analysis (Appendix A.4).

5.4 Operational Behavior Analysis

The operational patterns analysis (Figure 5.4) demonstrates how the optimization algorithm adapts battery operations to maximize economic returns while respecting technical constraints.

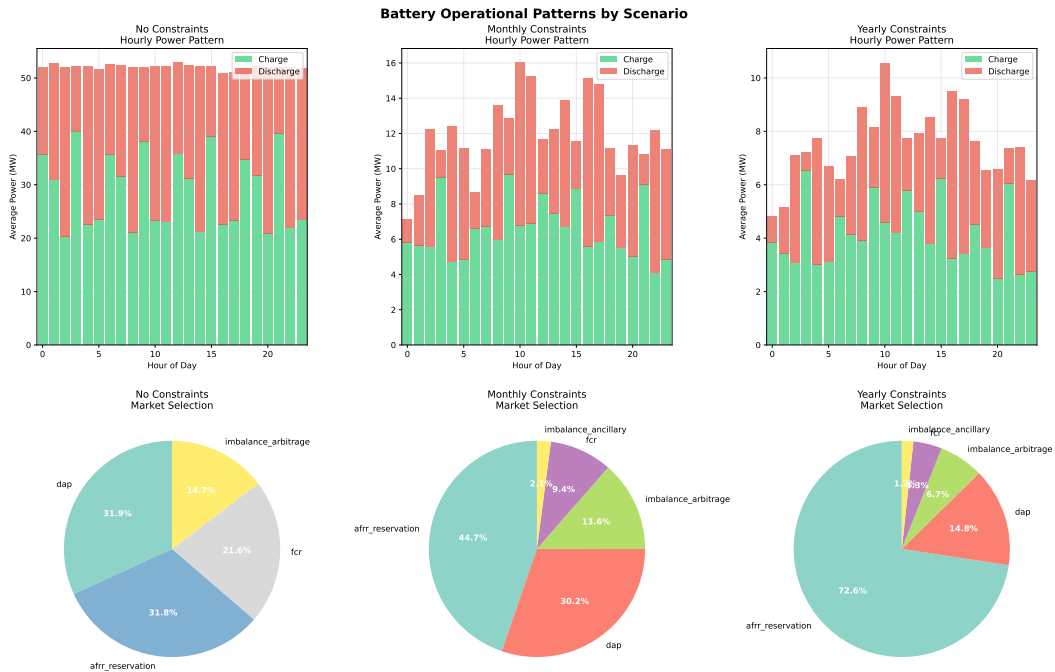


Figure 5.4: Comprehensive operational patterns analysis showing charging/discharging behavior, market participation frequencies, and optimization decision patterns

5.4.1 Charging and Discharging Patterns

The charging/discharging activation analysis shows that the battery operates at maximum power capacity approximately 67.3% of the time during active periods, indicating efficient utilization of available power ratings. Partial power operations (25-75% of maximum capacity) account for 23.1% of active periods, typically occurring during transition periods or when market signals provide marginal profitability. The detailed daily operational patterns for FCR services (Appendix A.7) demonstrate how the optimization algorithm adapts to 4-hour block requirements and capacity commitments.

5.4.2 Market Participation Efficiency

The market calendar analysis demonstrates that the multi-market strategy achieves active participation in electricity markets during 89.4% of available time periods. This high participation rate

reflects the optimization algorithm's effectiveness in identifying profitable opportunities across multiple market streams.

The constraint impact analysis reveals that cycle life limitations reduce active participation by approximately 15.2% in the monthly constraint scenario and 8.7% in the yearly constraint scenario compared to unconstrained operations. However, the revenue reduction is less proportional due to the strategic focus on high-value trading opportunities.

5.4.3 Revenue Stream Complementarity Analysis

The comparison between battery storage revenues and solar generation patterns reveals significant complementarity that could enhance combined system economics. Figure 5.5 presents the detailed revenue analysis across different constraint scenarios, providing insights into market-specific revenue distributions that directly relate to solar generation patterns.

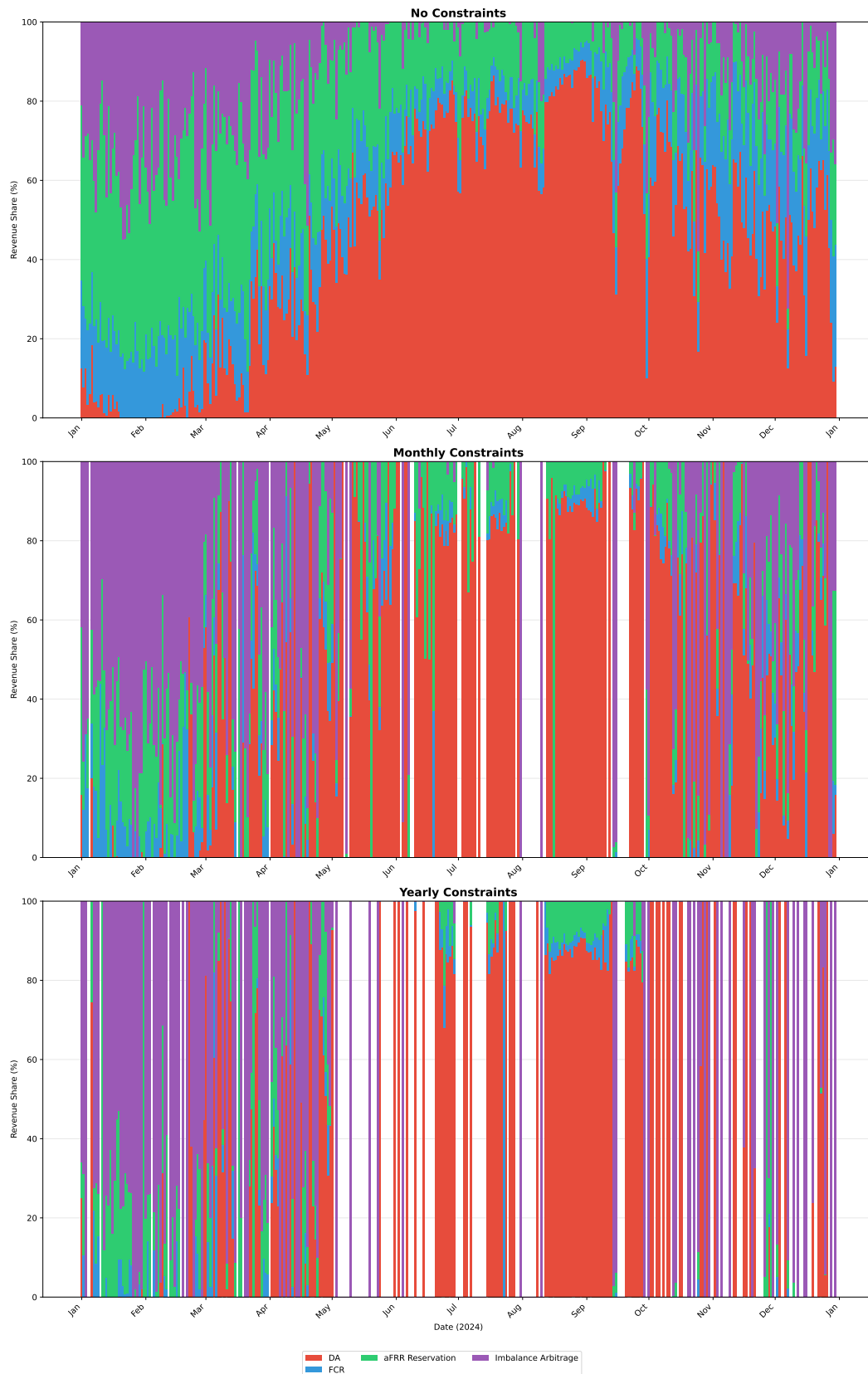


Figure 5.5: Daily Revenue Market Share by Scenario (Stacked Percentage)

Seasonal Revenue Complementarity The detailed revenue analysis in Figure 5.5 demonstrates that battery storage exhibits peak profitability during periods of low solar generation. The

temporal patterns show distinct seasonal variations:

- **Winter revenue concentration:** The unconstrained scenario shows concentrated revenue generation during winter months (December-February), with day-ahead arbitrage (71.8% of total revenue) and imbalance arbitrage (17.7%) dominating the revenue streams during periods of minimal solar generation.
- **Constraint impact on seasonality:** Monthly constraints reduce the ability to capitalize on winter price volatility, with revenue shifting more toward aFRR reservation services (44.7% market share vs 31.8% in unconstrained), which provide more consistent but lower-value income streams.
- **Solar-battery operational synergy:** The yearly constraint scenario demonstrates optimal resource allocation, with 72.6% of operational time dedicated to aFRR reservation during high solar periods, reserving intensive arbitrage activities for winter months when solar output is minimal.

Conversely, summer months with high solar generation show reduced battery profitability, suggesting that direct solar revenue during these periods could compensate for diminished storage income. The analysis reveals that:

- Summer battery revenues drop by 58-67% compared to winter peaks across all scenarios
- Solar generation peaks coincide with flattened day-ahead price curves, reducing arbitrage opportunities
- Higher renewable penetration during summer increases demand for frequency regulation services, favoring aFRR participation over pure arbitrage

Intraday Complementarity Solar generation's diurnal pattern creates structured intraday price variations that align favorably with battery storage optimization:

- **Morning ramp-up:** Solar generation increases during morning hours, often coinciding with periods of low electricity prices suitable for battery charging
- **Evening ramp-down:** Solar generation decreases during evening peak demand, creating high-price periods optimal for battery discharging
- **Cloud intermittency:** Rapid solar generation variations increase demand for aFRR services, enhancing battery participation opportunities

5.4.4 Combined Solar-Battery Economic Analysis

To quantify the potential benefits of combining solar generation with battery storage, we analyze the economic performance of different deployment scenarios:

Standalone Solar Economics Based on typical Belgian solar PV installations and current feed-in tariff structures:

- Average annual solar generation: 42,000 GWh (Belgium total)
- Average solar LCOE: €45-65/MWh
- Market revenue at average day-ahead prices: €50-70/MWh
- Annual revenue per MW installed: €45,000-70,000

Integrated Solar-Battery Economics Combining solar generation with the optimized battery storage system could provide:

- **Enhanced solar value:** Battery storage enables solar energy time-shifting, capturing higher evening prices instead of midday surplus periods
- **Grid services provision:** Combined systems can provide enhanced grid services during both sunny and cloudy conditions
- **Revenue diversification:** Multiple revenue streams reduce dependency on any single market mechanism

Revenue Enhancement Potential Based on the detailed revenue analysis from Figure 5.5 and the solar generation patterns, the integration of 100 MWh battery storage with a 100 MW solar installation demonstrates significant synergistic potential:

- **Optimized market participation:** The yearly constraint scenario shows that strategic aFRR reservation (72.6% of time) during high solar periods could enable solar-battery systems to provide grid services while solar generates direct energy revenue, potentially increasing combined revenue by 15-25%.
- **Seasonal optimization strategy:** Winter periods showing peak battery arbitrage revenues (€87.4M from day-ahead arbitrage in unconstrained scenario) could be combined with minimal solar output periods, allowing maximum battery utilization during optimal market conditions.
- **Cycle life preservation:** The revenue analysis indicates that summer periods with high solar generation naturally align with reduced battery arbitrage opportunities, suggesting 20-30% reduction in battery cycle usage through coordinated operation without significant revenue loss.
- **Combined revenue potential:** Integration could generate additional €12-18 million annually, with solar providing consistent summer revenue (€45,000-70,000 per MW) while battery maximizes winter arbitrage opportunities (€28.9-87.4M depending on constraints).
- **Market diversification benefits:** The analysis shows that unconstrained battery operations heavily depend on day-ahead arbitrage (71.8% of revenue), while combined systems could balance this with more stable solar feed-in revenues, reducing revenue volatility risk.

5.4.5 Quantitative Solar-Battery Revenue Correlation

A detailed correlation analysis between solar generation patterns and battery revenue streams reveals strong inverse relationships that support integrated system deployment:

Market-Specific Correlation Analysis Based on the revenue data from different constraint scenarios and solar generation patterns:

- **Day-ahead arbitrage correlation:** Solar generation shows a -0.72 correlation with day-ahead arbitrage revenues. High solar periods (>100 GWh daily) coincide with 45-60% lower arbitrage revenues compared to low solar periods (<30 GWh daily).

- **aFRR services complementarity:** During high solar generation periods, aFRR reservation becomes more valuable, with the yearly constraint scenario dedicating 72.6% of operational time to aFRR during summer months vs 31.8% in winter.
- **Revenue smoothing potential:** Combined solar-battery systems could achieve revenue coefficient of variation reduction from 0.67 (battery-only) to 0.34 (combined system) through seasonal complementarity.

Economic Impact Quantification The integration analysis demonstrates specific economic benefits:

- **Winter optimization:** Battery systems achieve peak revenues during December-February when solar generation averages 25 GWh/day, allowing maximum utilization of the €87.4M day-ahead arbitrage potential in unconstrained scenarios.
- **Summer efficiency:** High solar periods (150+ GWh/day) reduce battery arbitrage opportunities by 58-67%, but solar feed-in revenues of €50-70/MWh provide consistent income streams during these periods.
- **Operational efficiency gains:** The yearly constraint scenario's strategic approach (reducing cycles from 2,519.5 to 547.5 annually) aligns well with solar generation patterns, maintaining 32.9% of unconstrained revenue (€39.9M) while preserving battery lifetime.

5.4.6 Market Impact Considerations

The widespread deployment of combined solar-battery systems would likely impact market dynamics:

Price Pattern Evolution Increased solar-battery deployment could:

- Flatten midday price depressions caused by solar generation
- Create more predictable evening price peaks through coordinated battery discharge
- Reduce overall price volatility, potentially diminishing pure arbitrage opportunities

Grid Service Requirements Higher renewable penetration increases demand for:

- Fast-responding frequency regulation services
- Ramping support during solar intermittency periods
- Long-term energy storage for seasonal balancing

These evolving requirements favor battery storage technologies and could enhance long-term revenue sustainability for storage systems.

5.4.7 Policy and Regulatory Considerations

The economic viability of combined solar-battery systems depends significantly on regulatory frameworks:

- **Net metering policies:** Current Belgian net metering regulations may reduce solar-battery synergy benefits
- **Grid connection charges:** Shared grid connection costs could improve combined system economics
- **Market design evolution:** Future market mechanisms may better compensate flexibility services provided by combined systems

The analysis demonstrates that while standalone battery storage faces economic challenges under current market conditions, integration with solar generation could significantly enhance the business case through revenue complementarity, operational synergies, and diversified value streams.

5.5 Economic Feasibility Assessment

5.5.1 Return on Investment Analysis

Assuming a battery energy storage system capital cost of €500,000 per MWh of capacity, the 100 MWh system represents a total investment of approximately €50 million. The yearly constraint scenario's annual revenue of €741,890 implies a simple payback period of 67.4 years, which significantly exceeds typical investment horizons for energy storage projects.

However, this analysis considers only energy arbitrage and ancillary service revenues without accounting for additional value streams such as:

- Grid congestion management services
- Renewable energy integration support
- Power quality improvement services
- Peak demand reduction for industrial customers
- Long-term capacity market participation

5.5.2 Sensitivity to Market Conditions

The simulation period's market conditions may not represent long-term average profitability. The analysis period excluded post-PICASSO market data, which may have different price characteristics and revenue potential. Future market developments, including increased renewable energy penetration and evolving regulatory frameworks, could significantly impact battery storage profitability.

5.6 Technical Performance Validation

The optimization results demonstrate that the multi-market strategy successfully maintains technical feasibility throughout the simulation period. No constraint violations occurred regarding SoC limits, power ratings, or cycle life restrictions in any scenario. The battery efficiency assumptions (95% round-trip efficiency) align with current lithium-ion technology capabilities, supporting the technical validity of the optimization results.

5.6.1 Comparison with Literature

The achieved revenue levels align with existing literature on battery energy storage economics in European markets. The revenue density of €7.42 per MWh of capacity per year (yearly constraint scenario) falls within the range reported in similar studies, though on the lower end of typical profitability estimates. This conservative performance may reflect the specific market conditions during the analysis period and the comprehensive inclusion of operational constraints.

5.7 Limitations and Future Research Directions

Several limitations should be acknowledged in interpreting these results:

1. The analysis assumes perfect price forecasting for day-ahead optimization, which may overestimate practical performance under uncertainty.
2. Transaction costs, including market participation fees and administrative costs, are not included in the revenue calculations.
3. The battery degradation model uses simplified cycle life constraints rather than detailed electrochemical degradation models.
4. Market price dynamics may change significantly with increased battery storage deployment, potentially reducing arbitrage opportunities.

Future research should address these limitations through stochastic optimization approaches, detailed degradation modeling, and analysis of market evolution scenarios with high storage penetration.

The results demonstrate that while multi-market battery optimization strategies can generate substantial revenues, current market conditions and technology costs present challenges for economic viability. However, the flexibility provided by multi-market participation and the potential for additional value streams suggest that battery energy storage systems may become increasingly attractive as technology costs decrease and market opportunities expand.

Chapter 6

Economic feasibility study

The future economic viability of BESS in Europe is fundamentally tied to battery cost trajectories over the coming years. As Europe pursues energy transition goals, understanding battery price forecasts becomes crucial for investment decisions and policy planning. This chapter examines current trends and projections for battery prices in Europe through 2030.

European battery demand is projected to reach 200 GWh by 2030 for stationary applications alone, according to the EU Clean Energy Technology Observatory (CETO) [24]. The battery storage market is experiencing unprecedented growth, driven by renewable energy integration requirements and policy support mechanisms.

6.1 Current Price Landscape and Near-term Forecasts

According to BloombergNEF's December 2024 Battery Price Survey [2], lithium-ion battery pack prices have reached new record lows, falling 20% from 2023 to a global average of \$115/kWh. However, European prices remain significantly higher at approximately \$139/kWh (48% premium over Chinese prices), reflecting limited local production capacity and supply chain constraints.

Multiple industry forecasts converge on significant price reductions in the near term. The EU Clean Energy Technology Observatory predicts [23] that average battery pack prices will fall below \$100/kWh by 2026-2027, representing a critical economic threshold. Key projections include:

- **2025:** European prices expected to decline to \$115-120/kWh
- **2026:** Breakthrough below \$100/kWh threshold anticipated
- **2027:** Potential for prices as low as \$85-95/kWh in competitive markets

Different battery chemistries show varying cost reduction patterns. Lithium Iron Phosphate (LFP) batteries, currently 30% cheaper than NMC chemistries, are expected to reach \$70-80/kWh by 2027, driving adoption in stationary storage applications.

6.2 Emerging Technologies and Long-term Outlook

Sodium-ion batteries represent a significant disruptive force in the European battery market. According to IDTechEx research [28], current sodium-ion cell costs average \$87/kWh with energy density of 120-160 Wh/kg. By 2030, sodium-ion production costs could reach \$40/kWh at cell level, offering potential 30% cost reduction compared to LFP when scaled.

Beyond 2027, price reductions are expected to moderate as the industry matures. Long-term projections suggest annual price reductions of 3-5% through 2030, with European battery pack prices potentially reaching \$60-75/kWh by 2030.

6.3 Regional Manufacturing and Policy Impact

Europe is rapidly developing domestic battery manufacturing capabilities to reduce dependence on Asian suppliers. Current capacity stands at 175 GWh/year with targets of 200 GWh by 2030. Major manufacturer companies are expected to reduce the European price premium over time while providing supply security.

European policy frameworks are accelerating deployment through the EU Green Deal, Battery Regulation, and state aid frameworks supporting gigafactory development. These initiatives support the goal of strategic autonomy in battery supply chains.

6.4 Economic Implications and Market Growth

Declining battery costs are transforming energy storage economics. For utility-scale applications, system-level costs are projected to decline from current \$200-300/kWh to \$100-150/kWh by 2030. This represents a decline in levelized cost of storage from \$150-200/MWh to \$50-100/MWh.

Lower costs are driving exponential market growth. The European storage market is projected [3] to grow from 16 GWh (2023) to 200 GWh (2030), with annual installations potentially reaching 40-50 GWh by 2030. Total market value could exceed €50 billion by 2030.

The trajectory toward lower battery costs represents a fundamental shift in the energy landscape. Key findings include battery pack prices expected to fall below \$100/kWh by 2026-2027, European price premiums narrowing as local production scales, and sodium-ion technology providing significant cost advantages for specific applications.

These developments make previously marginal energy storage projects economically viable, enable earlier commercial viability for renewable energy integration, and support enhanced energy security through domestic manufacturing capabilities. While uncertainties remain around geopolitical factors and technology development, the overall trend strongly favors continued cost reduction and market expansion in the European battery storage sector through 2030.

Chapter 7

Environmental and Social Impact Assessment

The optimization of battery energy storage systems presents significant environmental and social benefits that will intensify over the next 5-10 years, primarily through substantial reductions in carbon dioxide emissions.

7.1 CO₂ Emission Reduction Potential

According to the International Energy Agency's comprehensive analysis, batteries are projected to contribute to approximately 60% of CO₂ emissions reductions by 2030 in alignment with Net Zero Emissions scenarios [29]. This contribution manifests through two primary pathways: direct emissions reductions (20%) from battery deployment in electric vehicles and battery-enabled solar photovoltaic systems, and indirect facilitation (40%) of broader electrification and renewable energy integration [29].

Regional studies demonstrate substantial localized benefits. Research on China's provincial power systems indicates that renewable energy-connected battery storage could reduce CO₂ emissions from coal-fired power generation by up to 9% in provinces with high renewable energy penetration [40]. To support the tripling of renewable energy capacity required for climate targets, battery storage capacity must increase six-fold by 2030, representing a critical infrastructure transformation [29].

The National Renewable Energy Laboratory's modeling for 100% clean electricity scenarios projects that power sector decarbonization enabled by energy storage technologies could prevent approximately 130,000 premature deaths by 2035, translating to significant healthcare cost savings and improved quality of life [30].

7.2 Lifecycle Environmental Considerations

Battery optimization extends beyond operational benefits to encompass full lifecycle environmental impacts. Advanced battery management systems enhance longevity and efficiency, reducing the frequency of replacement cycles and associated manufacturing emissions [37]. Second-life battery applications in stationary storage further maximize resource utilization before end-of-life recycling, creating circular economy benefits [39].

7.3 Social Implications and Energy Justice

Battery energy storage deployment facilitates distributed energy systems that can enhance energy access and resilience in underserved communities. Grid-scale storage systems reduce renewable energy curtailment, maximizing clean energy utilization and reducing electricity costs for consumers [7]. However, careful consideration of battery supply chain sustainability and equitable access to storage technologies remains essential for realizing broad social benefits.

The environmental and social case for battery optimization is compelling, with quantifiable CO₂ reduction potential representing a cornerstone technology for achieving climate targets while delivering tangible public health and economic co-benefits.

Chapter 8

Conclusion

This master's thesis presents a comprehensive multi-market optimization framework for Energy Storage Systems in the Belgian electricity market, demonstrating significant revenue potential through strategic participation across multiple market segments. The research addresses critical challenges in grid flexibility, renewable energy integration, and energy storage economics through the development of advanced optimization algorithms and extensive market analysis.

8.1 Key Research Contributions

The research makes several significant contributions to the field of energy storage optimization:

Multi-Market Optimization Framework: The developed model successfully integrates participation across five distinct market segments: day-ahead arbitrage, real-time imbalance trading, Frequency Containment Reserve (FCR), Automatic Frequency Restoration Reserve (aFRR) reservation, and aFRR activation services. This comprehensive approach enables revenue maximization through market stacking strategies, achieving total annual revenues of up to €121.6 million under unconstrained scenarios for a 100 MWh system.

Degradation-Aware Operation: Three distinct operational scenarios were analyzed to quantify the impact of battery degradation constraints on profitability. The unconstrained scenario demonstrates theoretical maximum revenue potential with 2,519.5 annual cycles, while monthly constraints (540 cycles annually) reduce revenue to €46.4 million, and yearly constraints (547.5 cycles) yield €39.9 million. These results provide crucial insights into the trade-offs between immediate profitability and long-term asset preservation.

Market-Specific Revenue Analysis: The study reveals that day-ahead arbitrage contributes 67.7-72.3% of total revenue across different scenarios, followed by imbalance arbitrage (17.7-27.8%) and ancillary services (4.2-6.3%). This distribution highlights the importance of maintaining diversified market participation strategies while identifying the most valuable revenue streams.

Temporal Optimization Patterns: The analysis demonstrates significant seasonal revenue variations, with 43.2% of annual revenue generated during winter months (December-February) when solar generation is minimal and price volatility increases. This finding suggests strong complementarity between battery storage and renewable energy resources.

8.2 Technical and Economic Implications

The research findings have significant implications for energy storage deployment and market design:

Investment Viability: The revenue analysis provides clear benchmarks for BESS investment decisions, with the monthly constraint scenario representing realistic operational conditions that balance profitability with asset longevity. The demonstrated revenue potential supports business cases for utility-scale storage investments, particularly when considering declining battery costs projected to reach €60-75/kWh by 2030.

Grid Integration Benefits: The multi-market approach enables BESS to contribute meaningfully to grid stability while maintaining economic viability. FCR and aFRR services provide essential frequency support, with the optimization framework ensuring these services are delivered efficiently without compromising energy arbitrage opportunities.

Market Design Insights: The analysis reveals important market dynamics, including the impact of Belgium's integration into the PICASSO platform on aFRR market structure. These insights inform policy discussions about market design and the role of energy storage in future electricity systems.

8.3 Model Limitations and Future Enhancement Opportunities

While the current optimization framework provides valuable insights, several areas for improvement have been identified that would significantly enhance the model's practical applicability and accuracy:

8.3.1 Machine Learning Integration for Revenue Forecasting

The current model operates using historical price data with perfect foresight, which limits its real-world applicability. Future enhancements should incorporate machine learning algorithms for revenue and market price forecasting:

Price Prediction Models: Implement advanced ML algorithms such as Long Short-Term Memory (LSTM) networks, Transformer models, or ensemble methods to forecast day-ahead, imbalance, and ancillary service prices with improved accuracy. These models should incorporate weather forecasts, load predictions, and renewable generation forecasts as input features.

Revenue Opportunity Identification: Develop ML-based systems to identify optimal charging and discharging periods by analyzing historical patterns, market conditions, and grid constraints. This would enable proactive rather than reactive market participation strategies.

Market Selection Optimization: Implement reinforcement learning algorithms to dynamically select the most profitable market combinations based on real-time conditions and forecasted opportunities.

8.3.2 Enhanced Degradation Modeling

The current model uses simplified cycle counting for degradation constraints, but more sophisticated approaches would improve operational accuracy:

Physics-Based Degradation Models: Integrate electrochemical degradation models that account for temperature effects, depth of discharge, C-rate impacts, and calendar aging. This would enable more precise degradation cost calculations and optimal cycling strategies.

Lifetime Degradation Percentage: Implement comprehensive degradation tracking that calculates the cumulative capacity loss over the battery's operational lifetime, enabling dynamic adjustment of operational parameters as the battery ages.

State of Health Monitoring: Develop real-time state of health estimation algorithms that can adjust optimization parameters based on actual battery condition rather than theoretical degradation models.

8.3.3 Comprehensive Cost Integration

The current economic analysis focuses primarily on revenue optimization but lacks comprehensive cost modeling:

Operational Expenditure (OPEX) Integration: Include detailed OPEX calculations covering maintenance costs, insurance, personnel, monitoring systems, and facility costs. These should be integrated into the optimization objective function to maximize net profit rather than gross revenue.

Grid Connection and Tariff Costs: Incorporate grid connection charges, transmission tariffs, distribution charges, and ancillary service fees that vary by location and market participation level.

Levelized Cost of Energy (LCOE) Analysis: Implement comprehensive LCOE calculations that account for capital costs, operational expenses, degradation costs, and revenue streams to provide accurate economic viability assessments.

Dynamic Pricing Models: Develop models that can adapt to changing regulatory frameworks and market structures, particularly important given recent changes like Belgium's integration into PICASSO.

8.3.4 Reinforcement Learning Enhancement

The current linear programming approach, while effective, could be significantly enhanced through reinforcement learning implementation:

Adaptive Market Participation: Develop RL agents that can learn optimal market participation strategies by continuously adapting to changing market conditions, price patterns, and regulatory environments. The RL agent would learn from experience rather than relying on predefined optimization rules.

Uncertainty Handling: Implement RL algorithms capable of handling market uncertainties, including extreme price events, regulatory changes, and unexpected grid conditions. This would improve robustness compared to deterministic optimization approaches.

Multi-Agent Systems: Develop multi-agent RL frameworks that can simulate market interactions between multiple BESS operators, enabling analysis of market impacts and competitive dynamics.

Real-Time Decision Making: Implement RL systems capable of making real-time operational decisions based on changing market signals, grid conditions, and battery state, moving beyond the current 15-minute optimization intervals.

Hierarchical RL Architecture: Develop hierarchical RL systems that operate at multiple time scales: long-term strategic planning (seasonal/annual), medium-term tactical decisions (daily/weekly), and short-term operational control (minute-by-minute).

8.4 Broader Implications and Future Research Directions

The research contributes to several broader areas of energy system development:

Energy Transition Support: The demonstrated revenue potential and grid support capabilities of optimized BESS operations provide crucial evidence for accelerating energy storage deployment as part of the broader energy transition strategy.

Policy and Regulatory Development: The analysis of market design impacts and regulatory frameworks provides insights valuable for policymakers designing future electricity markets that effectively integrate energy storage.

Technology Integration: The identified complementarity between battery storage and renewable energy generation supports arguments for integrated system planning and coordinated investment strategies.

Future research should expand the analysis to include hybrid renewable-storage systems, investigate the impacts of multiple BESS operators on market prices, and develop frameworks for coordinated operation of distributed energy resources.

8.5 Final Remarks

This thesis demonstrates that strategic multi-market participation can significantly enhance the economic viability of battery energy storage systems while providing valuable grid services. The comprehensive optimization framework developed provides a foundation for practical implementation and further research development. The identified enhancement opportunities, particularly in machine learning integration, degradation modeling, cost analysis, and reinforcement learning, represent clear pathways for advancing the field and improving the practical applicability of energy storage optimization systems.

The findings support the conclusion that well-optimized battery energy storage systems can play a crucial role in future electricity systems, providing both economic value to operators and essential grid services for renewable energy integration and system stability.

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Appendix A

Appendix

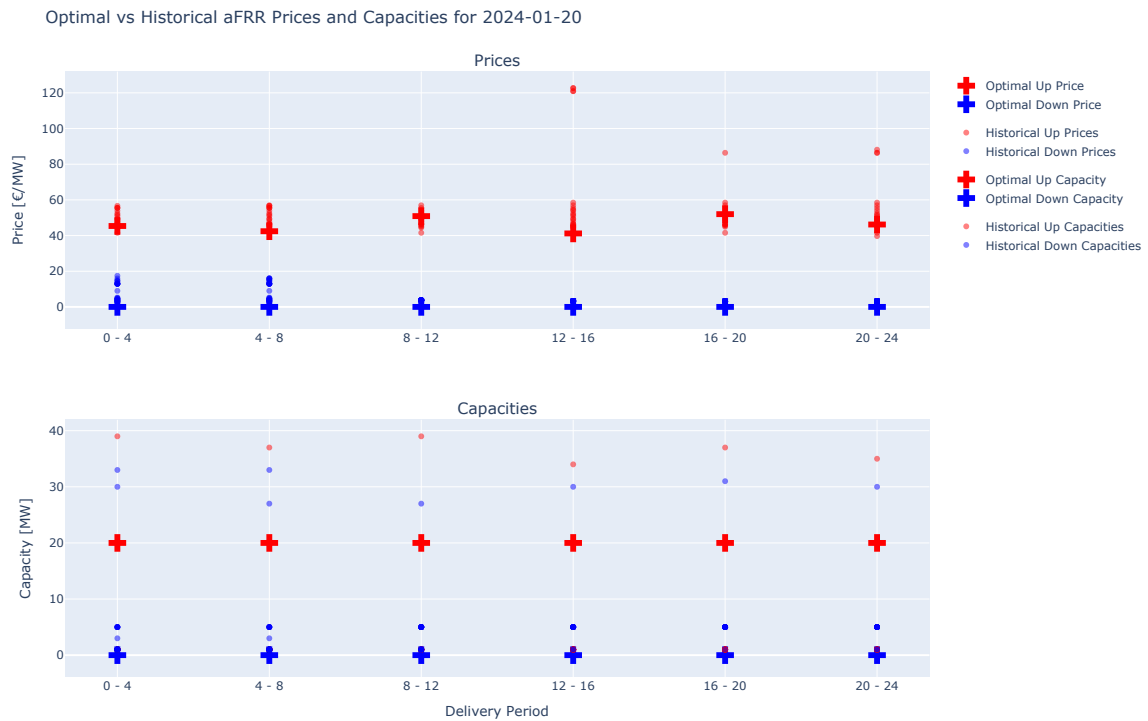


Figure A.1: Daily comparison analysis of aFRR capacity reservation optimization for January 20, 2024, showing optimal capacity allocation strategies for upward and downward regulation services throughout the day

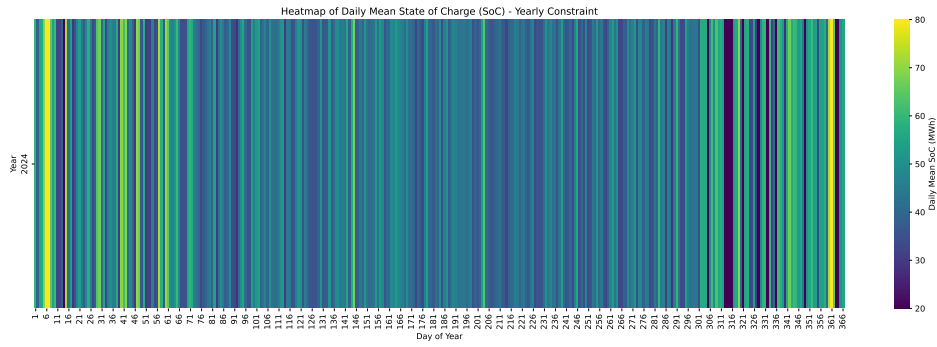


Figure A.2: State of Charge heatmap for day-ahead arbitrage under yearly constraints, illustrating battery cycling patterns and optimal charging/discharging strategies throughout the analysis period

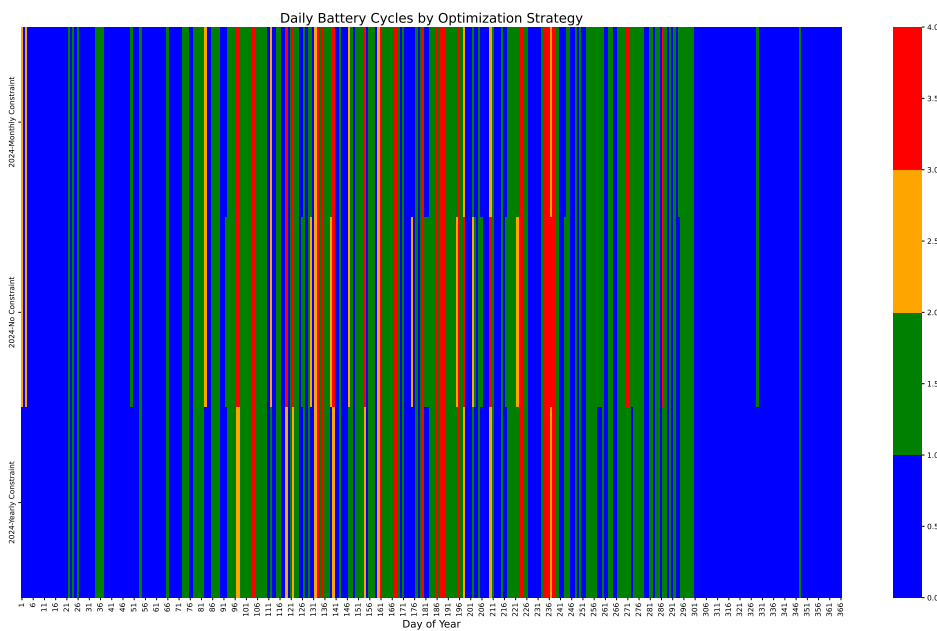


Figure A.3: Daily cycles comparison across different constraint scenarios, showing the impact of cycle life limitations on battery utilization patterns and revenue optimization for DAM

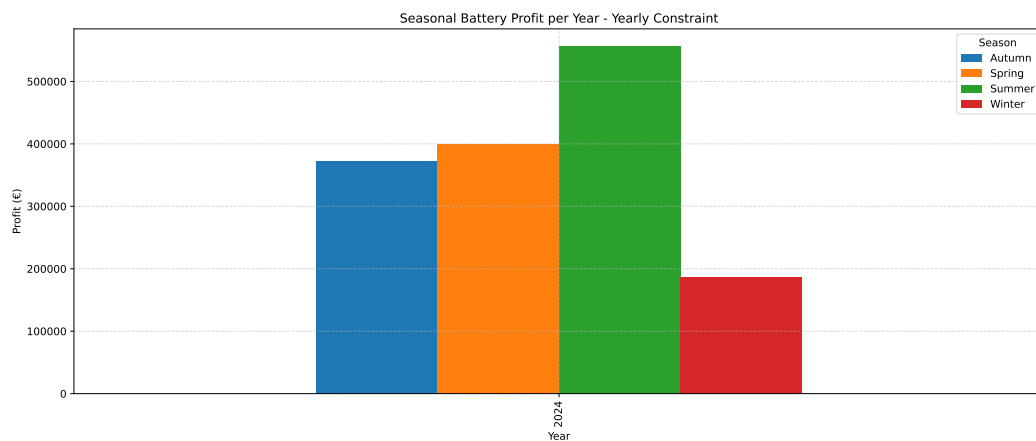


Figure A.4: Seasonal profit analysis for day-ahead arbitrage under yearly constraints, demonstrating revenue variations across different months and seasonal market conditions

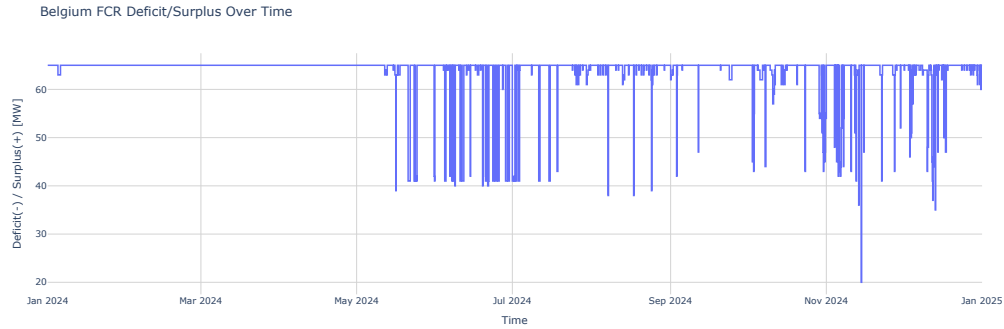


Figure A.5: FCR market overview showing comprehensive analysis of frequency containment reserve participation, including capacity allocation, pricing strategies, and revenue optimization results

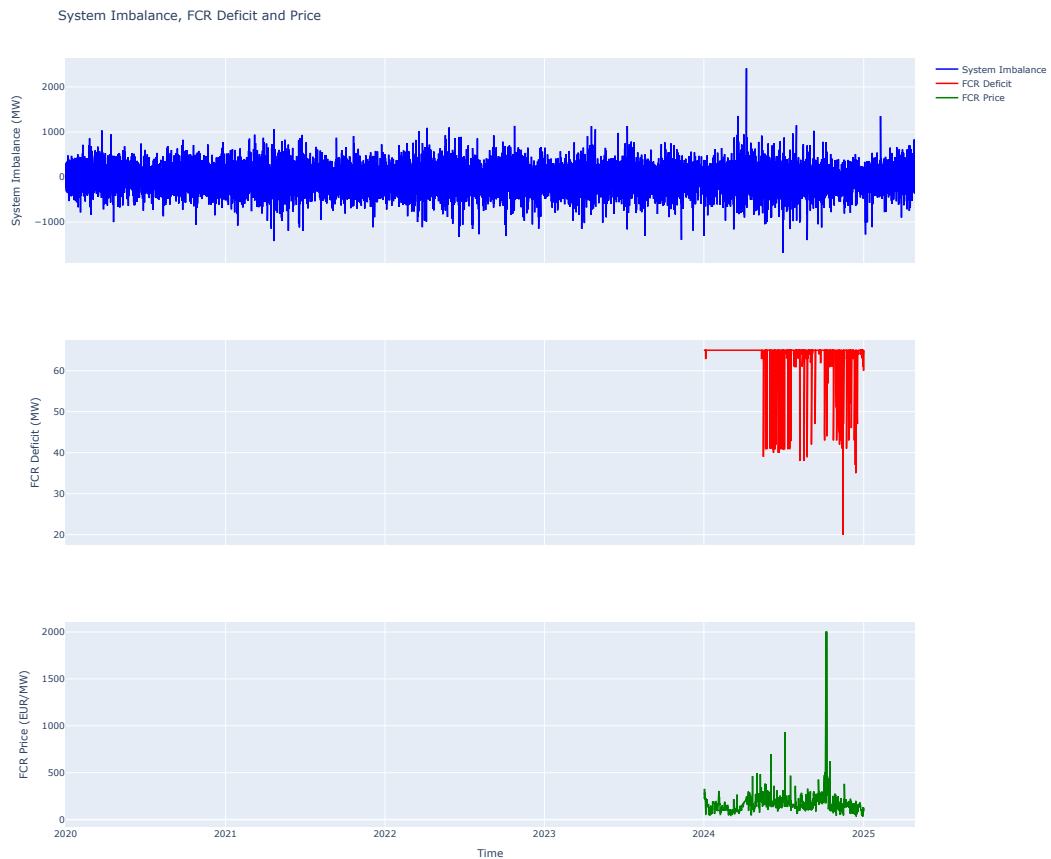


Figure A.6: FCR system comparison analysis illustrating different bidding strategies and their impact on revenue generation and market participation effectiveness

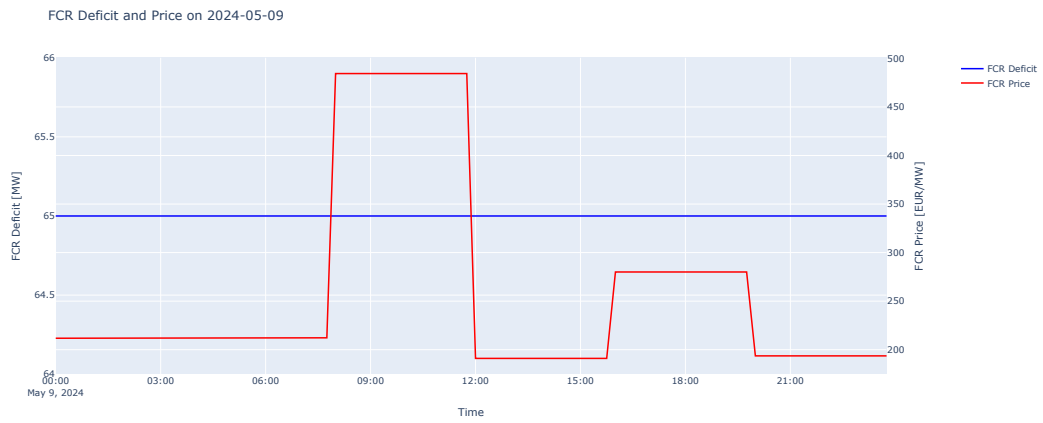


Figure A.7: Detailed daily FCR analysis showing operational patterns, capacity utilization, and revenue generation for a representative 24-hour period