FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Simulation of the Operation of Storage Devices in the Day-Ahead Market and in the Secondary Regulation Band Market

Guilherme da Silva Santos

Mestrado em Engenharia Eletrotécnica e de Computadores

Supervisor: Prof. João Tomé Saraiva

July 22, 2025

Abstract

The growing integration of variable renewable energy (VRE) sources into electricity grids poses significant challenges to system stability due to the inherent intermittency and unpredictability of generation. These challenges motivated the present study, which aims to evaluate the economic feasibility and operational viability of energy storage systems participating simultaneously in the day-ahead electricity market and the secondary regulation band market.

To address this, a simulation platform was developed using real historical data from the Iberian Electricity Market (MIBEL). The tool models the behavior of various storage technologies under different operating conditions, optimizing their participation across both market segments. The methodology integrates data processing, market price forecasting (assuming perfect foresight), and an optimization routine that balances energy allocation between the day-ahead electricity market and the secondary regulation band market, while accounting for technological constraints such as depth of discharge (DOD) and power to capacity ratios.

Simulation results using 2024 market data and 2023 storage cost data revealed that energy storage systems can generate positive returns when properly sized and strategically allocated between markets. Lithium Iron Phosphate (LFP) batteries showed the best performance among the studied battery technologies for medium-term investment scenarios. Meanwhile, Compressed Air Energy Storage (CAES) proved to be more suitable for large-scale, long-duration applications, standing out as the only consistently profitable solution at the time of the study.

The key findings underscore the importance of aligning technology selection with market strategies and investment objectives. Additionally, the results highlight the critical role of storage in enhancing grid flexibility, supporting VRE integration, and delivering ancillary services.

Overall, the study provides a valuable reference for investors, grid operators, and policymakers seeking to leverage energy storage systems for both economic benefits and improved grid reliability.

Resumo

A crescente integração de fontes de energia renovável variáveis (VRE) nas redes elétricas coloca desafios significativos à estabilidade do sistema, devido à sua intermitência e imprevisibilidade inerentes. Estes desafios motivaram o presente estudo, que tem como objetivo avaliar a viabilidade económica e a operacionalidade de sistemas de armazenamento de energia com participação simultânea no mercado diário de eletricidade e no mercado de banda de regulação secundária.

Para tal, foi desenvolvida uma plataforma de simulação com recurso a dados históricos reais do Mercado Ibérico de Eletricidade (MIBEL). A ferramenta modela o comportamento de diversas tecnologias de armazenamento sob diferentes condições operacionais, otimizando a sua participação nos dois segmentos de mercado. A metodologia integra o processamento de dados, previsão de preços de mercado (assumindo previsão perfeita) e uma rotina de otimização que equilibra a alocação de energia entre o mercado diário e o mercado de regulação secundária, tendo em conta restrições tecnológicas como a profundidade de descarga e a proporção entre a potência e a capacidade.

Os resultados das simulações, com base em dados de mercado de 2024 e custos de dispositivos de armazenamento de 2023, revelaram que os sistemas de armazenamento de energia podem gerar retornos positivos quando corretamente dimensionados e estrategicamente alocados entre mercados. As baterias de Fosfato de Ferro-Lítio (LFP) demonstraram o melhor desempenho entre as tecnologias de baterias estudadas para cenários de investimento a médio prazo. Entretanto, o Armazenamento de Energia por Ar Comprimido (CAES) revelou-se mais adequado para aplicações de grande escala e longa duração, sendo a única solução consistentemente rentável à data do estudo.

As principais conclusões reforçam a importância de alinhar a seleção da tecnologia com as estratégias de mercado e os objetivos do investimento. Adicionalmente, os resultados evidenciam o papel crítico do armazenamento na melhoria da flexibilidade da rede, apoio à integração de VRE e fornecimento de serviços auxiliares.

No seu conjunto, este estudo constitui uma referência valiosa para investidores, operadores de rede e decisores políticos que pretendam explorar o armazenamento de energia com o objetivo de obter benefícios económicos e reforçar a fiabilidade da rede elétrica.

UN Sustainable Development Goals

Sustainable development is crucial for long-term economic growth, environmental protection, and social well-being. It promotes resource conservation, reduces environmental degradation, and addresses climate change while advancing social equity and improving quality of life.

The United Nations has outlined 17 Sustainable Development Goals (SDGs). Through the energy sector, this dissertation contributes to three of the United Nations' SDGs:

- SDG 7: Ensure access to affordable, reliable, sustainable and modern energy for all;
- SDG 12: Ensure sustainable consumption and production patterns;
- SDG 13: Take urgent action to combat climate change and its impacts.

The main focus of this dissertation is on integrating energy storage systems into electricity markets. This integration enhances the use of renewable energy by preventing curtailment and waste, reduces reliance on non-renewable sources, lowers consumer costs, and supports the transition to a sustainable energy future.

SGD	**Target**	**Contribution**	**Performance Indicators and Metrics**
7	7.1	Optimally sized and operated storage units stabilize wholesale prices and recover excess renewable energy that would otherwise be curtailed.	Number of storage devices participating in the electricity market.
	7.2	Shifting the surplus renewable output into storage increases the net share of renewables delivered to consumers.	Decrease in annual renewable energy generation that is curtailed.
12	12.2	Capturing renewables variability turns it into a managed commodity, improving overall resource efficiency.	Decrease in annual renewable energy generation that is curtailed.
13	13.1	Storage systems enhance grid flexibility with rapid secondary reserve response, reducing risk of cascading outages.	Reduction in frequency and duration of grid imbalances and outages.

Acknowledgements

I want to express my deepest gratitude to everyone who contributed in various ways to completing this dissertation.

First and foremost, I sincerely appreciate my family. Their unwavering support, encouragement, and patience throughout this academic journey have been invaluable. To my parents, thank you for always believing in me, for your continuous motivation, and for providing me with the foundation to pursue my goals with confidence and determination.

I am profoundly grateful to my academic advisor, Professor João Tomé Saraiva. Your guidance, insightful feedback, and availability throughout this process have been crucial in shaping the direction and quality of this work. Our meetings and discussions significantly enriched the quality and relevance of this work. Your expertise and dedication to the field of energy systems are genuinely inspiring.

I would also like to thank Engineer Tiago Guerra from EDP – Gestão da Produção de Energia, S.A., for his encouragement, support, guidance, and inspiration along the way.

To my girlfriend, thank you for your unconditional support. Your encouragement has constantly reminded me of the importance of balance and perspective.

I also want to express my gratitude to my friends and university colleagues, particularly those from the Faculdade de Engenharia da Universidade do Porto (FEUP) and the Núcleo de Estudantes de Engenharia Eletrotécnica e de Computadores (NEEEC). Thank you for the camaraderie, the unforgettable moments, and the friendships I will cherish long after concluding this academic chapter.

Finally, I am thankful to all the professors, mentors, and fellow students who, directly or indirectly, contributed to my academic and personal growth during these years.

Thank you to all of you!

Guilherme da Silva Santos

Contents

List of Figures

List of Tables

List of Acronyms

aFRR	Automatic Frequency Restoration Reserve
AGC	Automatic Generation Control
AVR	Automatic Voltage Regulator
BC	Bilateral Contract
BESS	Battery Energy Storage System
CAES	Compressed Air Energy Storage
DOD	Depth of Discharge
FACTS	Flexible AC Transmission System
FCR	Frequency Containment Reserve
GenCo	Generation Company
LFP	Lithium Iron Phosphate
mFRR	Manual Frequency Restoration Reserve
MIBEL	Iberian Electricity Market
NMC	Nickel Manganese Cobalt
PHS	Pumped Storage Hydropower
REN	Redes Energéticas Nacionais
RFB	Redox Flow Battery
RR	Replacement Reserve
SC	Super Capacitor
SDG	Sustainable Development Goals
SMES	Superconducting Magnetic Energy Storage
STATCOM	Static Synchronous Compensator
SVC	Static VAR Compensator
TBE	Time to Break Even
TES	Thermal Energy Storage
VRE	Variable Renewable Energy
VRFB	Vanadium Redox Flow Battery

Chapter 1

Introduction

Electricity plays a fundamental role in the modern world, powering nearly every aspect of daily life, from homes and industries to transportation and communication systems. Its role is critical in enabling the transition toward a more sustainable future. As society increasingly relies on electrification to address environmental challenges and improve quality of life, the importance of reliable, efficient, and affordable electricity has never been greater.

Electricity markets play a crucial role in the modern economies by organizing the production, distribution, and commercialization of electricity in an efficient and secure manner. Liberalized markets, such as those in Europe, foster competition among generators and retailers, leading to more dynamic pricing and encouraging both responsible production and consumption [1].

1.1 Motivation

The increasing integration of renewable energy sources into the grids has brought environmental and economic benefits but also significant challenges due to their inherent production variability and unpredictability. This volatility and limited controllability of renewable energy production create mismatches between generation peaks and periods of higher demand, impacting the stability of the electricity grid [2].

Addressing these challenges is essential for ensuring grid stability and efficiency as renewable energy adoption continues to grow.

Energy storage devices play a critical role in addressing this issue by purchasing and storing excess renewable energy when it is abundant and inexpensive. This stored energy can then be transformed back to electricity and sold during periods of high demand and renewable energy supply is limited, leading to higher prices. This approach not only enhances grid stability but also creates a profitable opportunity to effectively manage the variability of some renewable energy sources, such as wind and photovoltaic.

In addition to mitigate these issues, investments in energy storage devices to hybridize renewable power plants are becoming increasingly common [3]. Storage devices not only provide flexibility but also help balance the grid during unforeseen consumption deviations. Additionally, current market structures offer financial incentives for entities that contribute to grid stability by providing energy reserves [4] [5], presenting an opportunity for further exploration and investment in energy storage solutions.

1.2 Objectives

This dissertation researches the economic feasibility of investing in energy storage by exploring their potential to generate profits through participation in the day-ahead electricity market while also allocating a portion of the storage capacity to the secondary regulation band market, serving as a secondary reserve for both energy production and consumption.

To this end, a range of storage technologies have been assessed in terms of performance characteristics and cost structure. Detailed simulations were performed across multiple market scenarios to quantify the profitability potential of having the flexibility to operate in both markets. These analyses also aim to highlight the broader role of storage assets in maintaining grid stability during periods of supply-demand imbalance. Therefore, multiple forecasting scenarios were analyzed to assess their impact on the profitability of energy storage systems.

The findings can be used to inform potential investors in energy storage technologies by determining whether energy storage systems are economically viable in the day-ahead and secondary regulation band markets and identify the conditions under which this investment provides optimal returns, benefiting investors while enhancing overall grid reliability and flexibility.

1.3 Document Structure

Apart from the Introduction, this document contains five additional chapters.

Chapter 2 provides a comprehensive review of the state of the art, introducing the key concepts that form the foundation of this research. It begins by examining the evolution and structure of the electricity market, highlighting current challenges that must be addressed. Particular attention is given to the operation of the day-ahead market and system services, as these are central to the scope of this study. This chapter also focuses on the Iberian Electricity Market (MIBEL), where the simulations are carried out. An overview of MIBEL's price evolution and the influence of renewable energy integration is presented to contextualize the analysis and support the relevance of the research within the current energy landscape.

Chapter 3 presents a comprehensive overview of various energy storage technologies, particularly in the context of grid-scale applications. The chapter is structured to introduce each technology's operating principles, technical characteristics, and its current or potential role in power systems.

Chapter 4 outlines the approach used to analyze the economic viability of storage technologies in electricity markets. It details the structure and logic of the developed simulation tool designed to model energy arbitrage and secondary reserve participation. This chapter also explains the tool's modular architecture, covering data inputs, optimization logic, and output metrics used for performance evaluation.

Chapter 5 presents the simulation setup and the results obtained using the developed tool. It includes the configuration parameters for each storage technology and market scenario, followed by a comparative analysis of economic performance.

Chapter 6 provides a reflection on the current state and future potential of energy storage systems in electricity markets. This chapter summarizes key findings from the study, discusses limitations, and proposes directions for future research.

Chapter 2

State of the Art

2.1 Electricity Market

The electricity market plays a vital role in the modern global economy by organizing the production, distribution, and commercialization of electrical energy. Broadly speaking, this market employs transaction mechanisms that enable the buying and selling of electricity while ensuring that generation continuously meets consumption in an economical, efficient, and reliable manner.

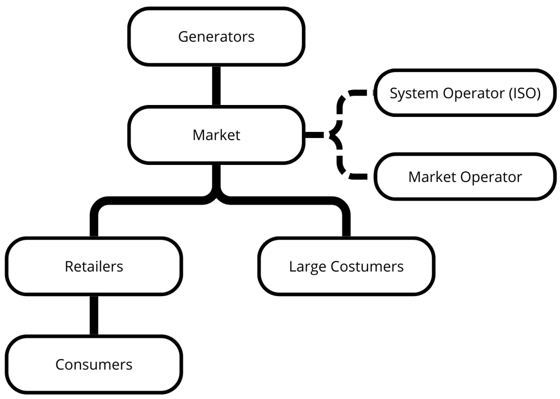


Figure 2.1: Simplified electricity market scheme

In many countries, reforms initiated in the 1990s led to the creation of decentralized electricity markets. These reforms facilitated the entry of new participants, such as independent power producers, and fostered healthy competition in the generation and retail sectors [1].

The European Network of Transmission System Operators for Electricity (ENTSO-E) is the association that brings together transmission system operators (TSOs) from across Europe. Its 40 member TSOs from 36 countries work together to ensure the secure and coordinated operation of the continent's electricity system. ENTSO-E's main responsibilities include the development and application of standards, network codes, platforms, and tools that support reliable system and market operations. It also plays a key role in integrating renewable energy sources and coordinating infrastructure planning through its European-wide ten-year network development plans [6].

The electricity market primarily consists of two main segments: the wholesale market, where electricity is produced and sold either to intermediary retailers or directly to large consumers who act as market agents themselves and the retail market, where energy is resold by retailers to final consumers. A simplified representation of this structure is provided in Figure 2.1 for a clearer visualization. Additionally, the market can be temporally divided into two segments: long-term and short-term markets [7].

Market operations rely on pricing mechanisms designed to incentivize both production and responsible consumption. This is achieved through auctions and long-term bilateral contracts, which ensure price stability and predictability. In the day-ahead and intraday markets, the pricing mechanism, commonly referred to as the spot energy market, plays a critical role in aligning supply with real-time consumption. Simultaneously, long-term contracts and energy storage solutions play a critical role in ensuring grid security whilst providing a safety net for investments in the sector [8].

Nowadays, the electricity market faces significant challenges associated with the integration of renewable energy sources like wind and solar and meeting decarbonization goals to support global environmental objectives. With increasing electrification and the decentralization of energy production, evidenced by the rise of distributed generation (where consumers also contribute, residually, to electricity production) [1], the sector is exploring innovative solutions to guarantee security and quality of supply. These include smart grid technologies and sustainable business models to address these evolving conditions effectively.

2.2 MIBEL

The Iberian Electricity Market (MIBEL), established in 2004, is the result of a collaborative effort by the Portuguese and Spanish governments to integrate their respective power systems and pre-existing electricity markets. MIBEL enables consumers across the Iberian Peninsula (mainland Portugal and Spain) to purchase electricity from any producer or retailer operating within the region under a competitive market framework. This market became a significant regional platform for electricity trading, characterized by its substantial growth in renewable energy production, pushing more expensive thermal power stations out of the wholesale generation schedule [9].

MIBEL operates through two main components: the forward markets, managed by the Iberian Energy Market Operator's Portuguese Division (OMIP), and the daily and intraday markets, managed by the Spanish Division of the Iberian Energy Market Operator (OMIE). This structure facilitates efficient trading and scheduling of electricity while supporting the integration of renewable energy sources into the grid [9].

In the Iberian Electricity Market (MIBEL), the day-ahead market serves as the primary platform for trading energy in Portugal and Spain, functioning as the central mechanism for integrating energy transactions. Bilateral contracts (BCs) complement this market by contributing to the overall operation and balance of the MIBEL energy production system. Together, they play a critical role in the operational and strategic decision-making of generation companies (GenCos) [10].

Within the context of the MIBEL, the participants in energy trading submit bids for selling or buying energy, either through the centralized market pool or through settling BCs with other MIBEL participants [10]. These bids, known as blocks, must specify the quantity of energy to buy or sell along with the corresponding price. Bids that only include the necessary information (quantity and price) are categorized as simple bids. Alternatively, market participants, namely generation agents, have the option to submit complex bids, which incorporate additional operational constraints such as minimum income conditions to recover fixed costs or technical parameters related to generation units, including ramp rates and the time required to transition between no-load and full-load states.

The GenCo interacts with two types of agents: International agents and MIBEL agents. Through international BCs linked to GenCo's global programming unit, the company is able to engage in cross-border energy trading with Morocco and France. Additionally, GenCo establishes BCs with other MIBEL agents, which may occur either before or after the day-ahead market [10].

Intraday markets play a critical role in enabling market agents to fine-tune their positions by submitting buy and sell offers to adjust their day-ahead schedules in line with their real-time operational needs [11].

Currently, there are two types of intraday markets: by auction and the European Continuous Intraday Market. Regarding the first mechanism, it is structured around six auction sessions under the MIBEL framework, supplemented by a European cross-border continuous market. They take place once the system operator has validated and, if necessary, adjusted the day-ahead market results to ensure technical feasibility [11].

As in the day-ahead market, once these intraday processes are concluded, the resulting schedules are forwarded to the system operators to support the planning and execution of balancing operations [11].

2.2.1 Evolution of Electricity Prices

Electricity prices play a pivotal role in the global economy, making it essential to mitigate sharp increases that may arise from geopolitical events or other external factors. In some scenarios, governments have the ability to adjust tax policies to alleviate potential crises. This approach was particularly evident in Europe during the early months of 2022, as illustrated in Figures 2.2 and 2.3.

The primary factors contributing to the sudden increase in electricity prices are the rise in natural gas prices (Figure 2.4), driven by geopolitical conflicts, and the rise in CO_2 emission rights certificate prices (Figure 2.5), implemented as an effort to combat the climate crisis.

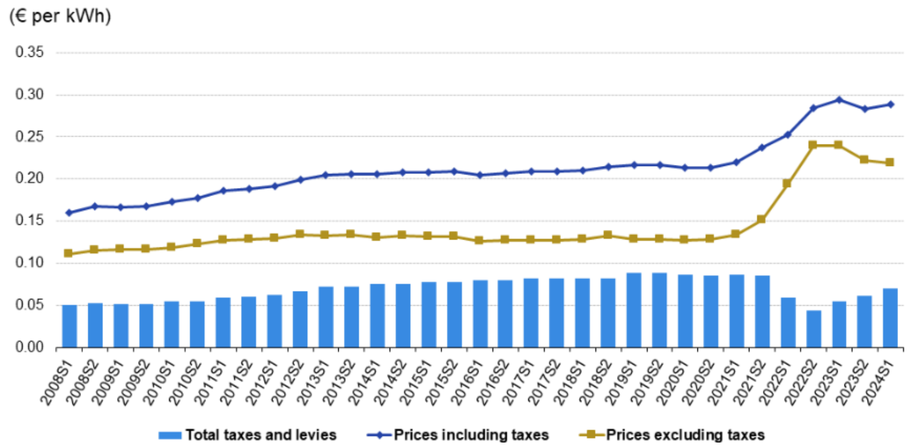


Figure 2.2: EU household consumers electricity price [12]

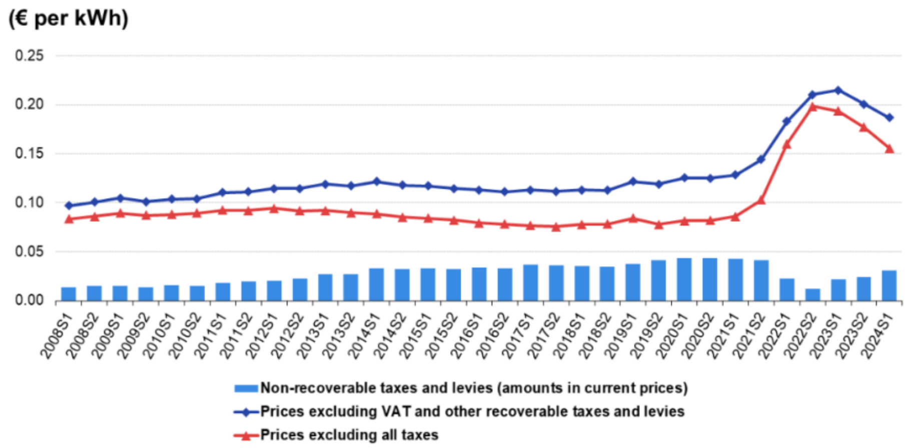


Figure 2.3: EU non-household consumers electricity price [12]

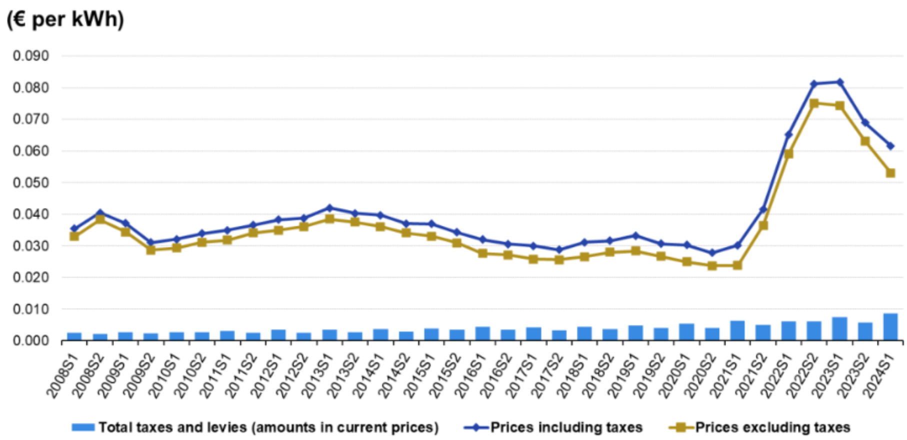


Figure 2.4: EU non-household consumers natural gas price [13]

Figure 2.5: EU carbon permits price (€/ton) [14]

The operation of the MIBEL relies on the availability of interconnection capacity that enables electricity exchanges in both directions, with minimal occurrences of network congestion. Typically, the prices are uniform within each market area unless congestion occurs in transmission lines, in which case a process known as market splitting is initiated.

Occasionally, the initial result generated by the market operator does not align with the capacity limits of the transmission lines. To address this issue, market splitting is applied. This process involves separately handling the buy and sell bids from each country, effectively running two distinct market simulations. As a result, two separate prices are established, one for each country. The importing market typically experiences a higher price, while the exporting market sees a lower price [8].

To address the dissertation problem, it is crucial to have abundant data about historical electricity prices to evaluate the long-term returns and to achieve accurate forecasts while optimizing the usage of the storage device in short-term transactions.

2.3 Day-Ahead Market

In the electricity sector, the day-ahead market serves essentially to balance supply and demand, ensuring short-term grid stability and optimizing resource allocation.

This market involves trading electricity one day before its actual production and delivery. Market agents submit bids indicating the volumes they wish to buy or sell for each hour, along with the corresponding price. Additionally, they can provide supplementary information, such as up and down ramps, as well as specific conditions, including startup and shutdown costs and the indivisibility of the initial block. When the demand is elastic, meaning it does not have to be totally supplied and that it reacts to price increases, the market operator solves a central welfare-maximization problem to match supply and demand, yielding both the dispatch schedule and the uniform clearing price for each zone. This process enables producers and consumers to plan their electricity generation and consumption in advance, therefore against price volatility, and ensure efficient utilization of generation capacity [15].

European market prices are typically cleared on a zonal basis, each zone often corresponding to a country or bidding area (since a country may be divided into one or more bidding areas), shown in Figure 2.6, where each zone has a single price and serves as the primary reference for wholesale electricity pricing [15].

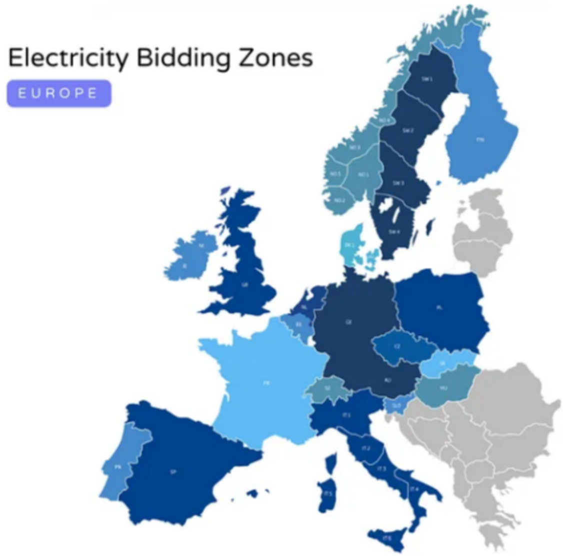


Figure 2.6: EU electricity market zones [15]

The formulation of the clearing problem for elastic and inelastic demand, represented by symmetric and asymmetric pools, is presented below. The symmetric pool objective is to maximize the total willingness to pay minus the total production cost, while the asymmetric pool minimizes the cost for a certain quantity of energy to be supplied. The resulting market prices for each hour are determined from the solution and reflect the value of balancing supply and demand. These prices come from the solution of the optimization problem considering various constraints. Subsequently, the standard definitions of consumer and producer surplus, and marginal price are derived, as well as the mathematical formulation of the optimization problem.

Symmetric pool objective function:

$$\max Z = \sum_{i \in D} P_{D_i} C_{D_i} - \sum_{j \in G} P_{G_j} C_{G_j} \tag{2.1}$$

Asymmetrical pool objective function:

$$\min Z = \sum_{j \in G} P_{G_j} C_{G_j} \tag{2.2}$$

Constraints:

$$\sum_{j\in G} P_{G_j} = \sum_{i\in D} P_{D_i} \tag{2.3}$$

$$0 \leq P_{G_j} \leq P_{G_j}^{bid}, \quad \forall j \in G \tag{2.4}$$

$$0 \leq P_{D_i} \leq P_{D_i}^{bid}, \quad \forall i \in D \tag{2.5}$$

$$P_{G_j}^{bid} \geq 0 \tag{2.6}$$

$$P_{D_i}^{bid} \geq 0 \tag{2.7}$$

where:

$G = \{1,2,\ldots,N_G\}$	set of generation bids
$D = \{1,2,\ldots,N_D\}$	set of demand bids
P_i^{bid}	quantity of bid i
P_i	accepted quantity of bid i
C_i	cost of bid i

Equation (2.1) aims to maximize the total willingness-to-pay minus the total generation cost. Equation (2.3) enforces energy balance, while constraints (2.4) and (2.5) impose bid quantity limits. Finally, constraints (2.6) and (2.7) establishes that all bids have positive quantities.

Maximizing the objective function ensures that generation is dispatched according to merit order, prioritizing the lowest-cost units first, while demand is cleared based on descending willingness to pay. This approach guarantees the greatest net benefit to society.

Mathematical formulation of the optimization problem [16]:

$$L = \sum C_i(P_{g_i}) - \lambda \cdot \left(\sum P_{g_i} - P_L\right) \tag{2.8}$$

$$\begin{cases} \dfrac{\partial L}{\partial \mathbf{P}_{g_i}} = \dfrac{\partial C_i}{\partial \mathbf{P}_{g_i}} - \lambda = 0 \qquad i = 1\ldots n \\ \dfrac{\partial L}{\partial \lambda} = \mathbf{P}_L - \sum \mathbf{P}_{g_i} = 0 \end{cases} \qquad \begin{cases} \dfrac{\partial C_i}{\partial \mathbf{P}_{g_i}} = \lambda \qquad i = 1\ldots n \\ \sum \mathbf{P}_{g_i} = \mathbf{P}_L \end{cases} \tag{2.9}$$

The marginal price refers to the incremental cost incurred from producing an additional unit of electricity if the load increases by one unit. Obtaining an optimal solution to this dispatch problem requires that the supply offers reflect the marginal production costs and that the demand bids represent the benefits each entity expects to derive from using electricity [16].

This price is fundamental to market clearing mechanisms, as it often determines the merit-order position of generating units. Moreover, it assumes a pivotal role in zonal pricing mechanisms, as it is the price paid to all generators whose offers are accepted, regardless of their production costs, provided their offer is below or equal to the marginal price. In liberalized electricity markets, such as those in Europe, this price forms the foundation for wholesale electricity transactions, promoting economic efficiency and incentivizing lower-cost generation.

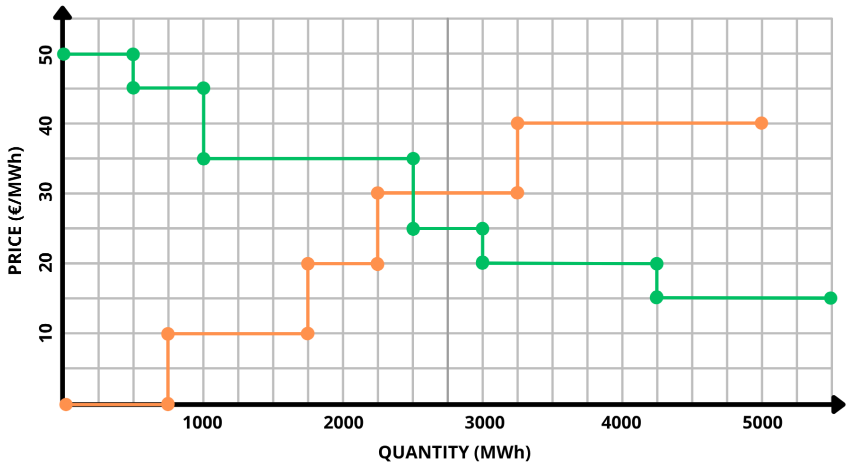


Figure 2.7: Example of the day-ahead market clearing problem for a given hour with elastic demand

Figure 2.7 represents, graphically, the market operator optimization problem for an hour of a day, considering only simple bids and elastic demand. Each segment represents a bid. The aggregated buying curve organizes bids by the descending order of the price while the aggregated selling curve organizes the bids by the ascending order of the price. The meaning of the intersection of buy (green) and sell (orange) aggregated curves is the cleared/marginal price for the specific hour of the day. All offers to the left of the intersection are accepted, and all the offers to the right are surplus.

An understanding of these market dynamics coupled with the interpretation of the graphic in Figure 2.7 is essential to manage the market and participate in daily electricity trading using a storage device effectively and profitably.

2.4 System Services

In the context of an increasingly interconnected and decarbonized European power system, one of the most recurring challenges in the electrical system is maintaining the balance between production and consumption. Given the frequent fluctuations in consumption levels, as well as variations in production driven by some renewable energy sources, it is common for production to not align perfectly with consumption. As a result, frequency oscillations occur, preventing proper stabilization [5].

To manage these imbalances and ensure stable grid operation, European countries now work together by sharing backup electricity across borders. This cooperation has become the cornerstone of keeping the power grid stable. Transmission System Operators (TSOs) rely on various types of frequency control reserves, like Frequency Containment Reserves (FCR), Frequency Restoration Reserves (aFRR and mFRR), and Replacement Reserves (RR), to maintain the system frequency closely around its nominal value.

To address this issue, there are system services designed to, in the short term, maintain equilibrium between production and consumption, while keeping the grid frequency as close to its nominal value as possible, allowing for minimal deviations. This control leverages active power reserves specifically designed to tackle this imbalance. These reserves are transacted in specific markets during the late afternoon, one day prior to the operational day [5].

To enhance the efficiency, reliability, and economic performance of reserve provision, the European Union has established a suite of cross-border cooperation mechanisms and market integration projects under the guidance of ENTSO-E and the electricity balancing guideline. Programs such as the FCR Cooperation [17], PICASSO [18], for aFRR, MARI [19], for mFRR, and TERRE [20], for RR, provide harmonized platforms for the exchange, activation, and settlement of balancing services across Member States. These programs enable the real-time optimization of system resources at the continental level, supporting both system stability and the European energy transition.

In Portugal, the national reserves are categorized as [4]:

- Primary Regulation Reserve (corresponding to FCR): Ensures rapid power adjustments by regulating the turbine speed in response to small frequency changes, stabilizing the system within 15 to 30 seconds.

- Secondary Reserve (corresponding to aFRR): Manages interconnection deviations with Spain or frequency corrections during island operation, with a response time of a maximum of 30 seconds and, situationally, finishing its operation within 5 minutes by action of the tertiary regulation.

- Regulation Reserve (corresponding to RR): Balances production and consumption during operational periods by adjusting power output based on demand deviations from the Overall System Manager's forecasts, maintaining required reserve levels.

Voltage offsets are addressed through automatic voltage regulators equipped with power system stabilizers and flexible AC transmission system (FACTS) devices, such as static VAR compensators (SVCs) and static synchronous compensators (STATCOMs), to effectively mitigate these oscillations. If not adequately damped, these oscillations can lead to partial or complete power system blackouts [21].

2.4.1 Voltage Control

Contrary to frequency, which is a system-wide parameter, voltage is a localized quantity that varies at each node within the power system. Voltage levels are influenced by factors such as system topology, the location of generators and loads, and the type of loads connected. The voltage in a power system is directly impacted by the balance of reactive power. To regulate voltage, reactive power injection is controlled using equipment such as automatic voltage regulators (AVRs), static VAR compensators (SVCs), capacitor banks, reactors, and on-load tap changer voltage transformers (OLTC) [21].

Due to the challenges associated with transporting reactive power over long distances, it is essential to manage voltage locally. Consequently, the placement of voltage control equipment in strategic locations within the power system is crucial to guarantee the stability of the system.

In Portugal, the energy management system provides real-time instructions for the operation of voltage control mechanisms, such as: requesting the supply or absorption of reactive power from generators, pump storage units and synchronous compensators, performing maneuvers on reactive compensation devices connected to the national transmission network or to the tertiary windings of transformers within the network, switching capacitor banks on or off, conducting maneuvers, and adjusting transformer tap changers.

In addition, providers of voltage control system services must inform the energy management system of any circumstances that could affect the availability or operation of their voltage control equipment [22].

In the majority of the cases, grid-connected generators are legally obligated to manage their reactive power generation or consumption, according to the network needs, as a non-remunerated service.

2.4.2 Primary Reserve of Frequency Control

The primary reserve is a form of frequency control that is activated locally and automatically through automatic generation control (AGC).

Essentially, this process involves the management of active power to minimize the mismatch between generation and consumption, which contains frequency deviations. This service must be activated within seconds of the occurrence of an imbalance and remain operational for a defined period [21].

In Portugal, this service is currently mandatory for the generators cleared in the market, and it is not paid.

2.4.3 Secondary and Tertiary Reserve of Frequency Control

The secondary reserve is a service designed to enhance the stability and reliability of the electrical grid. It is controlled by a centralized and continuous process managed by the Automatic Generation Control (AGC). The AGC has the capability to adjust the production of available units, modifying the active power output [5].

This service is remunerated, and traded in a dedicated market known as the secondary regulation band market [5]. This market facilitates the participation of dedicated devices, such as power generation units, flexible loads or storage devices, that can rapidly adjust their electricity production or consumption to respond to real-time grid demands. By doing so, these resources help maintain the balance between supply and demand, ensuring that the grid operates within safe and stable parameters, especially during critical periods of high variability or unexpected disruptions.

For each programming period for the following day, the system operator establishes the secondary capacity requirements for the grid operation [4]. Market agents interested in participating in this market are required to formulate and submit their offers. Each offer must specify the price the agent is willing to charge, expressed in €/MW, as well as the capacity they have available, typically measured in MW. These offers are evaluated within the market structure, and if an offer is accepted, the agent enters into a binding agreement. This commitment obligates the agent to provide or consume energy inside the regulation band to the grid whenever required, ensuring their resources are ready to meet the grid's operational needs [22].

The tertiary reserve is typically activated manually by the respective Transmission System Operators in scenarios where the secondary reserve is expected to be activated for an extended period. Its primary purpose is to release secondary reserves, but it can also serve as a supplement to the secondary reserve following major incidents, helping to restore frequency levels and subsequently releasing primary reserves as well. As previously mentioned, these reserves can be activated either manually at any time or in a scheduled manner. This type of control is also mandatory and remunerated through market mechanisms [5].

2.4.4 Blackstart

Black start operation is the process of restoring a power system, or a portion of it, to operational mode, following a partial or complete shutdown. Blackouts, defined as the total or partial loss of power in the system due to unpredicted transmission or generation failures, are the most undesirable scenarios for power systems, often resulting in significant social and economic losses [21].

Restoring the power system after a blackout involves a highly coordinated sequence of actions among various system components. This process is inherently complex due to the presence of numerous generators, loads, and transmission system constraints. In modern power systems, it is essential to identify generating units capable of operating without external support and ensure they can supply power locally to facilitate the restoration process [21].

The black start procedure involves three key steps [23]:

- the black start provider activates its auxiliary generator to energize the main generator and establish a power island using local demand;
- the black start provider energizes the transmission network to restore electricity supply to another non-black start provider;
- both black start and non-black start providers progressively restore demand across the system until complete restoration is achieved.

On 28 April 2025, a significant blackout disrupted electricity supply across Spain and Portugal, with minor, short-lived effects extending into border regions of France. Given the scale and cross-border impact of the event, it falls under the scope of Commission Regulation (EU) 2017/1485, which mandates coordinated reporting, investigation, and operational compliance among European transmission system operators [24].

In Portugal, the response to the incident involved multiple regulatory frameworks. National obligations under the Directorate General for Energy and Geology (DGEG) include maintaining security of supply and implementing risk preparedness plans. Concurrently, the Quality of Service Code, as defined by ERSE's Regulation 826/2023, governs sectoral performance and recovery standards [24].

REN successfully restored full operation of the National Electricity Transmission Network leveraging blackstart capabilities from two key facilities that are contracted for blackstart services [24].

This event underscores the critical role of regulatory coordination and strategic investments in system resilience, particularly in maintaining rapid restoration capabilities through blackstart infrastructure.

2.5 Renewable Energy

Electricity generation has historically relied on fossil fuels, which offer a concentrated and stable energy supply that can be stockpiled for immediate use when needed. Similarly, hydro and geothermal energy provide reliable, stable forms of renewable energy. In contrast, intermittent renewable sources, such as wind, wave, tidal, and solar, cannot be stockpiled and must either be used as they are generated or converted into a form of energy that can be stored to prevent losses [25].

Load following in power systems involves adjusting generation to match fluctuations in electricity demand throughout the day. This is achieved by gradually increasing or decreasing generation output or by bringing additional generation sources on/off line as needed. Such adjustments are usually performed by generators with fast ramping capabilities or the flexibility to start or stop within tens of minutes. Variable Renewable Energy (VRE) sources, such as solar and wind, generate power based on the availability of renewable resources and are not inherently designed to follow load. However, when paired with energy storage systems, they can contribute to load-following capabilities [26].

As the energy sector transitions to higher percentages of renewable electricity generation, the deployment of effective energy storage technologies becomes critical. These systems are necessary to capture and retain energy from intermittent sources until it is required. With advancements in energy storage solutions, renewable energy can replace fossil fuels and represent a sustainable energy grid [25].

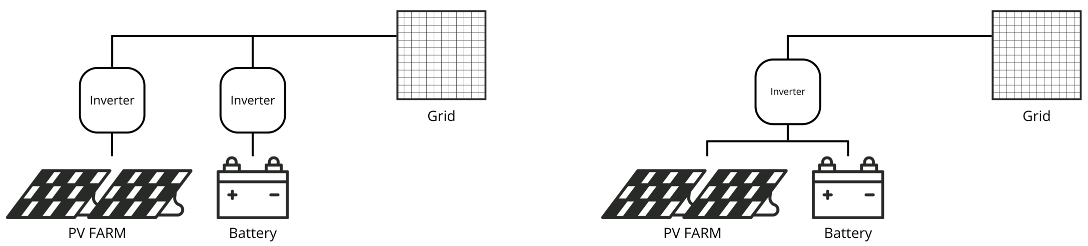
Scheduling in power systems involves planning and allocating generation resources to meet daily energy and peak demand requirements. This process relies on forecasting daily demand and scheduling appropriate generation while maintaining adequate reserve margins. In systems with high penetration of VRE, accurate forecasting of renewable resource availability and output becomes critical to ensure reliable and efficient operation. Effective scheduling strategies are essential to address the variability and uncertainty introduced by VRE sources [26].

Adopting grid scale storage systems also enhances efficiency by addressing the mismatch between peak demand, which typically lasts only a few hours each day, and traditional over-engineered power plants that are designed to operate at a production rate far exceeding the average base load. Additionally, energy storage plays a vital role in applications like grid stability and operational support. In an era of advanced technical equipment, ensuring an uninterrupted power supply is more critical than ever.

2.5.1 Power Plant Hybridization

Hybridization refers to the process of combining different energy generation and storage technologies within a single renewable energy facility to optimize performance, enhance efficiency, and make better use of available resources, including grid resources.

Renewable power plants frequently operate below their maximum connection capacity due to the inherent variability of renewable energy resources. By incorporating hybridization, unused connection capacity can be effectively leveraged through the integration of complementary technologies, such as battery storage, illustrated in Figure 2.8, to enhance grid efficiency and reliability. These hybrid systems not only enable a more consistent energy supply but are also adaptable to evolving energy policies, market dynamics, and technological advancements, ensuring their long-term sustainability and competitiveness [3].



(a) Introducing the battery and its respective inverter in parallel with the plant

(b) Introducing the battery in parallel with the plant, using a single inverter

Figure 2.8: Simplified scheme of PV plant hybridization

Chapter 3

Storage Technologies

Energy storage technologies have been extensively researched and implemented at both grid and individual levels due to the numerous advantages they offer.

Energy storage technologies are assessed using various technical-economic indicators that facilitate comparison across different systems. The most commonly used indicators include investment cost per unit of energy or power, maintenance cost, operational lifetime, energy and power density, total energy and power capacity, round-trip efficiency, response time, ramp rate, life cycle, self-discharge rate, and depth of discharge [27].

3.1 Chemical and Electrochemical Storage

3.1.1 Chemical Energy Storage

Chemical energy storage, particularly hydrogen and its derivatives, has significant promise in a decarbonized energy system. Hydrogen is especially well-suited for long-duration energy storage due to its low energy capacity cost. Beyond storage, hydrogen offers additional value streams through sector coupling, where it can support decarbonization in industrial processes and transportation. For example, clean hydrogen could meet demands for industrial heating, transportation, and maritime or aviation fuel [28].

Key insights about hydrogen's role in the power sector include:

- Hydrogen production, storage, and consumption can occur without CO_2 emissions.
- Low capital costs and high technological advancements across the hydrogen value chain make it a viable option for long-duration energy storage.

However, long-duration energy storage may not be the primary driver of future hydrogen demand. Instead, hydrogen's ability to electrify sectors that are hard to decarbonize, such as heavy industry and long-distance transport, will likely drive its adoption. Additionally, the competitiveness of hydrogen for power generation remains limited due to the availability of cheaper natural gas-powered assets [28].

Below is a photograph of a chemical energy storage facility commissioned in Sweden [29].

Figure 3.1: Hydrogen Storage Plant in Svartöberget, Luleå, Sweden [29]

3.1.2 Advantages of Electrochemical Storage Over Other Energy Storage Methods

Electrochemical energy storage systems are among the most efficient, sustainable, and environmentally friendly solutions for clean energy storage [30].

Compared to thermal and mechanical energy storage technologies, electrochemical energy storage devices offer a significant edge in energy density, surpassed only by chemical energy storage. Battery systems deliver more energy for a given area, have fewer site constraints, are simpler to design and achieve equivalent economies of scale [28]. At the moment, the leading solutions to electrochemically store energy are batteries and capacitors [30].

3.1.3 Li-ion Battery

Li-ion batteries are highly suitable for short-duration grid storage due to their optimal combination of energy density, power density, and efficiency. However, alternative chemistries like redox flow batteries (RFBs) or metal-air batteries have inherently lower material costs and allow for more flexible energy scaling versus power, making them increasingly viable for long-duration applications [28].

Li-ion batteries lead the scalable electrochemical storage units, offering the best energy and power density per footprint. For grid applications, energy density constraints are less critical, enabling the use of more abundant materials (e.g., manganese, iron, phosphorus, silicon, and sulfur), which continues to drive cost reductions across all applications [28].

Currently, Li-ion batteries' cycle and calendar life remain to limit certain grid applications, particularly those requiring infrequent or prolonged discharge. This challenge impacts return on investment and restricts their use in less predictable or long-duration scenarios [28].

Below is a photograph of a Li-ion battery facility commissioned in Australia [31] [32].

Figure 3.2: 150MW Lithium Battery Hornsdale Power Reserve, Australia [31] [32]

3.1.4 Redox Flow Batteries (RFBs)

RFBs provide a unique advantage by decoupling power and energy, making them ideal for scaling to larger systems and supporting long-duration storage. While various chemistries are possible, vanadium-based RFBs represent the industry standard, offering high energy density, low maintenance requirements, and long operational life [28].

However, the cost and availability of vanadium pose challenges for broader adoption. Although vanadium RFBs dominate current installations, their scalability may be constrained as demand grows and resource costs rise [28].

3.1.5 Metal-air Battery

Metal-air batteries use abundant materials like zinc, iron, or aluminum and aqueous electrolytes, resulting in low material and energy costs. While they generally have lower roundtrip efficiency and higher power costs compared to Li-ion and RFB systems, their ability to support long discharge periods makes them attractive for applications with infrequent usage patterns [28].

The predominant batteries to be considered in this category are Zinc-air batteries, which are the most studied ones, and iron-air batteries, which are gaining traction for future development [28].

3.1.6 Lead-acid Battery

Lead-acid batteries are comparable to Li-ion batteries in upfront costs but fall short in cycle life and calendar life. However, their established recycling infrastructure is a notable advantage. To remain competitive for investors, lead-acid technologies must improve their cycle life, especially at deeper discharge depths [28].

3.1.7 Super Capacitor

Electrochemical capacitors, also known as super capacitors (SCs), exhibit a combination of properties from both batteries and traditional capacitors. As a result, SCs can complement or, in some cases, replace batteries in certain applications. This dual functionality has driven extensive research into materials that combine the characteristics of batteries and capacitors, aiming to achieve fast charging, exceptional cycling stability, and the ability to meet high energy and power demands. The objective is to maximize energy storage capacity while maintaining the high power density and long cycling stability inherent to capacitors [30].

3.2 Mechanical and Gravity Energy Storage

Most gravity energy storage sources can also be categorized as mechanical energy storage since its main principle relies on lifting a mass to a higher elevation (mechanical work), which increases its gravitational potential energy. This stored energy is released when the mass is lowered, typically driving a generator to produce electricity.

Pumped hydroelectric storage facilities represent the most well-established form of gravity-based energy storage. However, there has been a growing interest in alternative gravity storage solutions, including systems that utilize lifts, cranes, and abandoned mines [27].

There are also strictly mechanical energy storage methods, such as compressed air energy storage (CAES), which benefits from being carbon neutral, having convenient manufacturing with a short construction period, high operational efficiency, and low investment risk [33].

The majority of these approaches provide low energy density, which is a crucial limitation for a variety of scenarios and reduces their competitiveness compared to other energy storage technologies [28].

Below is a photograph of a mechanical energy storage facility commissioned in the Hebei Province in China [34].

Figure 3.3: 100MW Compressed Air Energy Storage (CAES) in Zhangjiakou, Hebei Province, China, image by IET [34]

3.3 Thermal Energy Storage

Thermal energy storage (TES) offers the potential for long-duration energy storage by leveraging inexpensive materials with high thermal performance to store heat. The primary challenge lies in efficiently and cost-effectively converting stored heat back into electricity. Advancements in thermal-to-electrical conversion technology are critical for TES to become viable in grid-scale applications [28].

3.4 Magnetic Energy Storage

Magnetic energy storage, particularly Superconducting Magnetic Energy Storage (SMES), is an innovative and efficient approach to storing electrical energy using the principles of electromagnetism. SMES systems rely on superconducting coils that can sustain an electrical current indefinitely without energy loss, provided the system remains at temperatures as low as 4K. This enables the storage of energy in the magnetic field generated by the current in the coil. The use of High-Temperature Superconductors have further advanced SMES technology, enabling operation at higher temperatures (30–40 K) and magnetic flux densities, which reduces cooling costs and improves overall efficiency [35].

With power ratings ranging from 100 kW to 10 MW and exceptional cycle efficiency (95%), SMES offers fast response times (5 milliseconds), long operational lifetimes (30 years), and the ability to discharge energy over durations ranging from minutes to hours. These characteristics make SMES a highly reliable solution for various applications, including voltage control, reactive power compensation, and grid stability enhancement [35].

Despite its potential, challenges such as high initial investment, material improvements, and cooling system optimization remain key areas for further development. Nonetheless, SMES represents a promising solution for a sustainable, high-performance energy storage system [35].

3.5 Comparison of Storage Technologies

Selecting the appropriate storage technology is key to making optimal use of the device when performing its intended application, as each technology's technical–economic profile suits different roles, as shown in Table 3.1. Technologies are broadly classified by their deployment scale (grid-scale, distributed, or local) and integration mode (centralized or decentralized) [27].

Grid-scale energy storage systems include pumped hydro energy storage, compressed air energy storage, power-to-gas systems such as hydrogen storage, and thermal solutions like concentrated solar power. These systems have the ability to absorb off-peak energy and supply during high-price periods and are typically used for grid-level energy management and large-scale energy integration [27][36].

On the other hand, distributed and local storage systems are more suited for localized or individual applications. Examples include supercapacitors (SCs), superconducting magnetic energy storage (SMES), hydrogen-based solutions like hydrogen fuel cells, and thermal storage systems [27][36].

Certain storage technologies are applicable across both scales due to their versatility and modular deployment, being ideal for maintaining power quality through grid disturbances. These technologies include conventional batteries, flow batteries, high-temperature batteries, flywheels, and gravity-based storage systems, and they are frequently referred to as bridging technologies [27][36].

Table 3.1: Qualitative comparison of storage technologies using the technical-economic indicators [27] [36]

	Cost per unit of energy	Cost per unit of power	Total Capacity	Efficiency	Discharge Duration	Life Cycle
Hydrogen	Very low	Low to Medium	Very Low to High	Very Low to Medium	High	Low
Li-ion	Medium to High	Medium to High	Very Low to High	Very High	Medium	Low to Medium
RFB	Medium to High	High	Low to High	High	Very High	Medium
Lead-acid	Medium	Very Low to Low	Very Low to High	Medium to Very High	High	Very Low to Low
SC	High	Very Low	Low to Medium	Very High	Very Low	Medium to Very High
PHS	Medium	Medium to Very High	Very High	High	Very High	Medium
CAES	Low to Medium	Low	Very High	Medium	Very High	Medium
SMES	Very High	Very Low	Low to High	Very High	Very Low	Medium

Chapter 4

Methodology

4.1 General Aspects

This chapter describes the tool developed for calculating the income provided to a storage device via the participation in the day-ahead and secondary reserve markets. The developed tool is a Python-based program, its functionalities are detailed in chapter 4.

The program uses historical data to find the optimal scenario for using a given storage device by accurately representing its insertion in the day-ahead and secondary reserve markets.

Throughout the program's development, multiple versions were implemented, progressively enhancing accuracy and optimization, although it noticeably increased the computational cost. The substantial volume of input data, combined with the amount of calculations performed, results in a considerably high time consumed to optimize a realistic scenario for a user-defined storage device.

Even though the goal was to achieve perfectly accurate results, some small adjustments were made to reduce computational time and program complexity. Nevertheless, it was assured that every approximation made considered the worst case.

The final version of the program is composed of four main functions:

- Data Manipulation;
- Day-Ahead Market Profit Calculation;
- Secondary Reserve Market Profit Calculation;
- Results Optimization.

These functions articulate with each other ensuring cohesiveness (Figure 4.1), for example, when it is assured that the participation in the secondary regulation and day-ahead markets can't occur simultaneously, since it is assumed that the connection power limit is achieved every time a transaction is in progress.

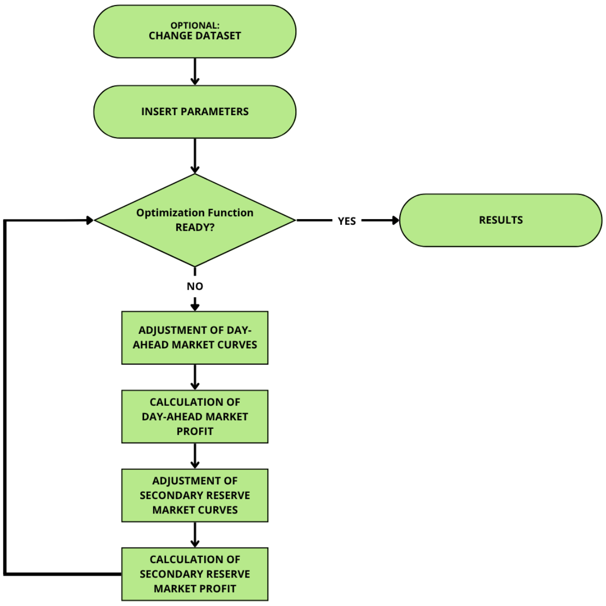


Figure 4.1: Structure of the developed simulation tool

4.2 Versatility and Restrictions

When running the program, the user is able to choose the storage device capacity, the power of connection to the grid and the depth of discharge, all of which will impact market prices of both markets and, consequently, the income results.

A lower power-to-capacity ratio will reduce the versatility of the BESS due to the number of hours that it takes to fully charge/discharge the device, but it will also be cheaper to acquire. A more in-depth view of the optimization of this proportion is provided in Chapter 5.

The historical data that the user wants the program to analyze must be provided by OMIE or must have a similar structure, both in the document's name and content. Assuming that this restriction is followed, the program can run its analysis properly for any set of historical data or even forecast.

4.3 Data Manipulation

The quality of the data fed to the program is one of the main factors that will influence the accuracy of the simulation results.

The excerpt of code presented in Figure 4.2 represents how the data is retrieved from the files provided from OMIE database.

```python
def read_curves(folder_path: str) -> pd.DataFrame:

    all_data = []
    for fname in os.listdir(folder_path):

        path = os.path.join(folder_path, fname)

        day_ahead_curves = pd.read_csv(
            path,
            sep = ';',
            skiprows = 2,
            usecols = ['Hora','Tipo Oferta','Energía Compra/Venta','Precio Compra/Venta','Ofertada (O)/Casada (C)'],
            encoding = 'ISO-8859-1')

        day_ahead_curves['Energía Compra/Venta'] = (
            day_ahead_curves['Energía Compra/Venta']
            .str.replace('.', '', regex=False)
            .str.replace(',', '.', regex=False)
            .astype(float))

        day_ahead_curves['Precio Compra/Venta'] = (
            day_ahead_curves['Precio Compra/Venta']
            .str.replace('.', '', regex=False)
            .str.replace(',', '.', regex=False)
            .astype(float))

        date_match = fname[-10:-2]
        day_ahead_curves["Data"] = pd.to_datetime(f'{date_match[:4]}-{date_match[4:6]}-{date_match[6:]}')
        all_data.append(day_ahead_curves)

    return pd.concat(all_data, ignore_index=True)
```

Figure 4.2: Developed data manipulation of day-ahead market offers

4.4 Day-ahead Contribution Calculation

Fundamentally, the main goal when transacting in the day-ahead market relies on submitting buying offers when the price is expected to be the lowest and selling offers when the price is expected to be the highest.

For real life practice the usage of this type of operation relies on the accuracy of price forecast, but for simulation purposes the timing used to place buy and sell offers assumes a forecast accuracy of 100%.

The developed program comes with a function specifically to carry out the calculation.

Before selecting the periods to place the selling bid(s), the hourly prices for the day-ahead are recalculated considering an extra bid from the battery placed at 0€/MWh with the respective capacity for each hour. The cleared price for buying bid(s) also needs to be adjusted with a similar procedure, although the bid is placed at the highest price possible. A simplified explanation of the steps taken in the case of the selling bids is as follows:

- Order contracted bids from the lowest to the highest price;
- Remove contracted bids with highest prices that cover at least the energy offered by the storage device;
- Set the new price for the respective hour according to the highest price contracted from the remaining offers.

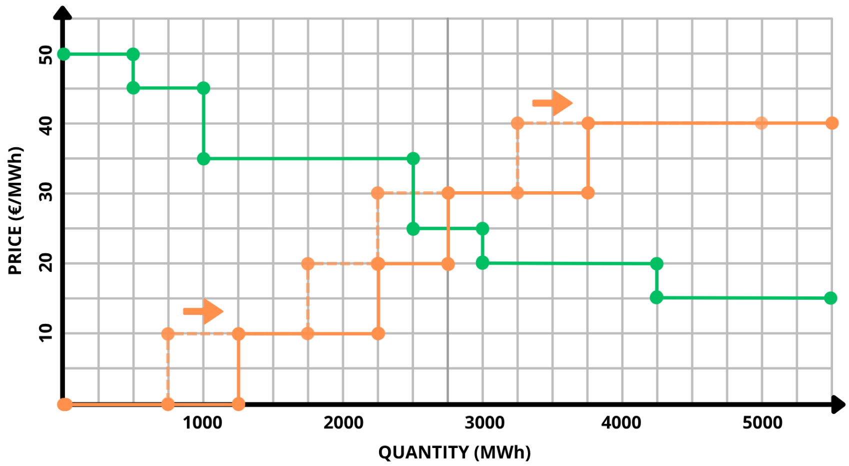


Figure 4.3: Example of integrating a storage device's selling bid in the day-ahead market clearing problem

After that, the time to place the bids to buy and sell energy for a given day is placed according to Equation 4.1.

$$H_{buy}, H_{sell} = Max\{Price_{Hour_{sell}} - Price_{Hour_{buy}}\} \quad , H_{buy} < H_{sell} \tag{4.1}$$

Where, H_{buy} is the hour selected to buy the energy and H_{sell} is the hour selected to sell the energy. It is important to note that the power of the storage device is taken into account in the entire process, which means that if the power is lower than the capacity, the program will take into account the need for 2 or more hours to fully charge and discharge the device.

4.5 Secondary Reserve Contribution Calculation

The implemented script simulates a single daily participation in the secondary reserve market. While this could be increased, provided the storage device maintains sufficient capacity between participations, a single hourly participation was chosen to simplify coordination between the two simultaneous market interactions.

The hour selected to bid in the secondary reserve market corresponds to the hour that provides the highest price after recalculating it, including the storage device offer, during which the battery is not already operating.

The recalculation of the prices for the secondary reserve market is similar to the one done in the day ahead market. However, instead of starting from the highest price and removing offers until the offered capacity is reached, due to the different format of the data, it was more optimal to start with the capacity offered and add the lowest price offers until offered power amounts to the necessity defined by the operator.

In the secondary reserve market, the agent is paid for the power they can provide or consume for at least one hour. The market operator determines the price per megawatt (MW) based on forecasted needs and submitted offers, similar to the day-ahead market.

Payment in the secondary reserve market is based on the available power, regardless of whether that power is used or not. Since reserve activation depends on unpredictable frequency deviations caused by production-demand mismatches, actual usage is difficult to forecast and was not simulated in the program. In any case, apart from the payment by the cleared power regulation band, in Portugal the activated energy inside that band is paid at the price of RR reserve for each hour. The battery controller must always ensure sufficient energy to provide or leave space to store energy, according to the proposed offer, in case the operator activates the reserve. These pre-adjustments, along with any actual energy transactions, are assumed to balance out financially. Because there is no optimization involved in this process, simulating these transactions was deemed unnecessary for the developed program.

4.6 Optimization of Battery Capacity Distribution

From a computational point of view, the function responsible for the heaviest part of the code is the optimization of the percentage dedicated to each market. This operation requires that the calculation of the profit of both markets is performed 11 times (from 0% to 100% in steps of 10%) iteratively for each day and is responsible for storing the profits of the best case, as long as the respective percentage.

Chapter 5

Results

5.1 Data Considered

All the simulation results presented in this chapter were developed using the historical data of the whole year 2024 of MIBEL. This includes all the bids for the day-ahead and secondary regulation markets, as well as the final results with final prices for each hour of the day. Data related to the day-ahead market was acquired from OMIE database [37], which is an official operator of MIBEL, and data related to the secondary reserve market was acquired from REN [4].

As it was previously mentioned in Section 4.2, the data to input in the program must comply with the format provided by these entities (OMIE and REN) that can be seen in the following Figures.

Data	Hora	Unidade Física	Quantidade Subir [MW]	Quantidade Descer [MW]	Preço [€/MW]
2024-01-05	12	GVAES	80.00	40.00	74.15
2024-01-05	13	GVAES	80.00	40.00	212.62
2024-01-05	13	POCINHO	59.00	29.50	0.00
2024-01-05	14	GVAES	80.00	40.00	209.59
2024-01-05	15	CARRAPA	64.00	32.00	50.10
2024-01-05	15	RIBEIRD	12.00	6.00	26.58
2024-01-05	16	CARRAPA	64.00	32.00	63.85
2024-01-05	16	GVAES	80.00	40.00	227.63
2024-01-05	17	RIBEIRD	11.00	5.50	35.78
2024-01-05	18	GVAES	80.00	40.00	70.00
2024-01-05	18	GVAES	80.00	40.00	70.35
2024-01-05	18	GVAES	80.00	40.00	70.70
2024-01-05	18	RIBEIRD	11.00	5.50	26.56
2024-01-05	19	GVAES	80.00	40.00	70.70
2024-01-05	22	VALEIRA	50.00	25.00	26.82
2024-01-05	23	GVAES	80.00	40.00	44.37
2024-01-05	2	VALEIRA	44.00	22.00	27.80
2024-01-05	3	CARRAPA	31.00	15.50	31.06
2024-01-05	2	RIBEIRD	11.00	5.50	15.62
2024-01-05	4	GVAES	80.00	40.00	71.05
2024-01-05	4	POCINHO	19.00	9.50	0.00
2024-01-05	5	GVAES	80.00	40.00	78.74
2024-01-05	5	VALEIRA	66.00	33.00	0.00
2024-01-05	6	RIBEIRD	9.00	4.50	19.04
2024-01-05	8	GVAES	80.00	40.00	70.70
2024-01-05	9	FTUA	11.30	5.70	20.00

Figure 5.1: Data provided by REN of the past bids in the secondary reserve market

```
Hora;Fecha;Pais;Unidad;Tipo Oferta;Energía Compra/Venta;Precio Compra/Venta;Ofertada (O)/Casada (C);
1;29/11/2024;MI;TOTRM01;C;386,3;1.500,00;O;
1;29/11/2024;MI;TOTRM03;C;80,4;1.500,00;O;
1;29/11/2024;MI;TOTRM02;C;91,1;1.500,00;O;
1;29/11/2024;MI;ZELTC01;C;0,2;800,00;O;
1;29/11/2024;MI;HCGCOX;C;1,2;701,00;O;
1;29/11/2024;MI;STROC01;C;0,1;700,05;O;
1;29/11/2024;MI;ALDRC02;C;34,2;501,00;O;
1;29/11/2024;MI;ALDRC01;C;258,1;501,00;O;
1;29/11/2024;MI;GEDPGC2;C;1.903,0;501,00;O;
1;29/11/2024;MI;IGESC2;C;1.037,6;500,00;O;
1;29/11/2024;MI;GSMGC1;C;2,7;500,00;O;
1;29/11/2024;MI;EGLEC2;C;380,1;500,00;O;
1;29/11/2024;MI;AXPOR01;C;10,9;500,00;O;
1;29/11/2024;MI;ICLIR01;C;101,2;500,00;O;
1;29/11/2024;MI;ICLIC01;C;611,1;500,00;O;
```

Figure 5.2: Data provided by OMIE of the past bids in the day-ahead market

The costs considered for the economic analysis of storage devices were acquired from the Pacific Northwest National Laboratory (PNNL) [38], that provides average discriminated values of the prevailing market prices in 2023, as well as conservative, realistic, and optimistic forecasts for 2030, for a variety of storage technologies.

5.2 Storage Device Optimization

Storage device acquisition prices are usually measured in €/MWh, and generally, this price decreases significantly with the increase of the installed capacity.

However, an increase in the storage device capacity will inevitably have a higher impact on the prices of the market and, consequently, negatively affect profit.

To sum up, on the one hand, an increase in storage device capacity acquisition will lower initial costs, but on the other hand, it will also lower the yearly revenue. This duality raises another optimization problem.

5.2.1 Evaluation of Storage Technologies for the Study

The Pacific Northwest National Laboratory provides a variety of meaningful data, such as a breakdown of costs and performance relative to different storage technologies [38]. In this study, all the technologies that had similar parameters to allow for a fair comparison were considered. The technologies considered were:

- Compressed Air Energy Storage (CAES);
- Pumped Storage Hydropower (PSH);
- Thermal Energy Storage (TES);
- Vanadium Redox Flow Battery (VRFB);
- Lead Acid Battery;

- Lithium-ion Battery (LFP);
- Lithium-ion Battery (NMC).

The main difference between LFP and NMC batteries is their chemical composition. This difference makes LFP batteries more efficient, more environmentally friendly, and cheaper, while the main advantage of NMC technology is its higher power density [39], being more suitable for space restrictive applications, which is not the case of this study.

The overall cost of the different technologies is divided into three main categories. Fixed costs include the acquisition of all the equipment necessary to integrate the storage device in the grid, as well as the storage device itself. Operating costs that represent all yearly expenses, such as maintenance, keeping devices operational, warranty and, in some cases, insurance. End-of-life or decommissioning costs, which are usually referred to battery systems, include the removal and recycling of the equipment.

The different technologies evaluated also differ in performance factors like calendar life, efficiency, and depth of discharge (DOD) with the respective life cycle, which will be considered in this section to properly/more accurately evaluate what is the more economically favorable technology to consider in this kind of study. Below we detail the breakdown of the previously mentioned performance factors.

- Calender Life: Maximum amount of time the system remains functional, not considering operating conditions;
- Efficiency: Ratio of the amount of energy that the system can deliver relative to the amount of energy received;
- DOD: percentage of a battery's total capacity that is discharged relative to its maximum rated capacity during a full cycle. This is an important indicator associated with each storage technology. In fact, manufacturers advise that the discharge should not go beyond the maximum specified DOD in order to ensure safe operation and to prevent early degradation;
- Life Cycle: number of complete charge-discharge cycles a system can perform at a specified DOD before its capacity degrades below the specified DOD.

Table 5.1: Cost and performance of different storage devices technologies considered for the study [38]

	Power (MW)	Capacity (MWh)	Fix Cost (M$)	Yearly Cost (M$)	Eff.	Life (yrs.)	DOD (%) (cycles)
CAES	100	400	109.0	1.70	0.55	60	80
PSH	100	400	270.3	2.72	0.8	60	80
Thermal	100	400	276.1	3.07	0.48	33	80
VRFB	100	400	273.5	1.32	0.65	12	80 (5250)
Lead Acid	100	400	181.5	0.48	0.77	14	68 (2368)
Lith (LFP)	100	400	150.1	0.43	0.83	16	80 (2400)
Lith (NMC)	100	400	165.4	1.65	0.83	13	80 (1520)

Observing the data in Table 5.1, storage technologies can be divided into two categories: battery and non-battery technologies. Among non-battery technologies, thermal storage is the least attractive due to its higher costs, low efficiency, and shorter calendar life compared to the other two. On the other hand, between pumped storage and compressed air, it is not immediately clear which is the most optimal technology for the study, as one offers lower costs but also lower performance. Therefore, the technologies were compared by integrating performance metrics in the costs of both technologies:

$$\frac{CAES}{PSH} = \frac{FixCost_{CAES} + YearlyCost_{CAES} \cdot Life_{CAES} \cdot \frac{1}{Eff_{CAES}}}{FixCost_{PSH} + YearlyCost_{PSH} \cdot Life_{PSH} \cdot \frac{1}{Eff_{PSH}}} = \frac{384}{542} \tag{5.1}$$

Even considering the higher efficiency provided by PSH compared to CAES, compressed air energy storage is still the most adequate choice for this study.

Now, for the different battery technologies, the Lead Acid and Lithium-ion NMC batteries will not be considered since they both have higher costs and lower performance when compared to the Lithium-ion LFP battery.

It is not immediate to access the optimal technology among VRFB and LFP batteries since they have different life cycles. If a similar calculation as the one performed in non-batteries technologies was performed, the VRFBs would present a higher cost, although, because they have a higher life cycle, it is possible that the revenue in that period of time would be sufficient to cover the higher cost, meaning that, in this case, it is not possible to formulate a definitive conclusion just by observing the costs.

This means that depending on the type of investor and application of the storage device, LFP batteries, VRFBs, or CAES should be the preferred choice for this kind of strategy, with the batteries best for mid-term investment (about 10 years) and CAES for long-term investment (more than 20 years).

Aiming at establishing a fair comparison between the three most promising technologies, an in-depth analysis is performed in Section 5.4.

Table 5.2: Cost and performance of different sizes for a Lithium-ion LFP system [38]

Lith (LFP)	Power (MW)	Capacity (MWh)	Fix Cost (M$)	Yearly Cost (M$)	Eff.	Life (yrs.)	DOD (%) (cycles)	Total Cost (M$/MWh)
2h	100	200	85.1	0.26	0.83	16	80 (2400)	0.446
4h	100	400	150.1	0.43	0.83	16	80 (2400)	0.392
6h	100	600	217.4	0.60	0.83	16	80 (2400)	0.378
2h	10	20	9.1	0.03	0.83	16	80 (2400)	0.477
4h	10	40	16.3	0.05	0.83	16	80 (2400)	0.426
6h	10	60	23.7	0.06	0.83	16	80 (2400)	0.411

To calculate the total cost of a specific case the expression (5.2) was used.

$$TotalCost = \frac{FixCost + YearlyCost * Life}{Capacity} \tag{5.2}$$

Despite Table 5.2 being associated to a LFP battery system the other technologies previously considered present a similar behavior. From the table above, it can be concluded that there is a correlation between the price per MWh and the acquired capacity: the price tends to decrease as the system size increases. Additionally, the data also indicate that prices become progressively lower as the power-to-capacity ratio decreases.

5.3 Simulation Results

The simulations aimed to obtain results that are as close as possible to a real scenario, requiring the most reliable and updated data regarding the offers and prices of both day ahead and secondary reserve markets. The dataset used to simulate the behavior of the storage device includes the historical data of MIBEL during the entire year of 2024.

The developed application delivers to the user results containing both daily detailed results and a summary of the results in the dataset provided, which in this case would be related to the profit in the year 2024, not considering acquisition and operational costs. The user receives a report, represented in Figure 5.3, containing the daily results with the chosen capacity to dedicate to each market, the total daily profit and the profit from each market.

```
2024-12-15 → Secondary Reserve: 70%, DA Profit: €28.49, Secondary Profit: €164.95, Total: €193.45
2024-12-16 → Secondary Reserve: 70%, DA Profit: €30.11, Secondary Profit: €91.49, Total: €121.61
2024-12-17 → Secondary Reserve: 70%, DA Profit: €18.90, Secondary Profit: €137.08, Total: €155.98
2024-12-18 → Secondary Reserve: 30%, DA Profit: €53.76, Secondary Profit: €22.83, Total: €76.59
2024-12-19 → Secondary Reserve: 0%, DA Profit: €163.84, Secondary Profit: €0.00, Total: €163.84
2024-12-20 → Secondary Reserve: 70%, DA Profit: €25.02, Secondary Profit: €82.45, Total: €107.47
2024-12-21 → Secondary Reserve: 0%, DA Profit: €134.76, Secondary Profit: €0.00, Total: €134.76
2024-12-22 → Secondary Reserve: 0%, DA Profit: €105.15, Secondary Profit: €0.00, Total: €105.15
2024-12-23 → Secondary Reserve: 0%, DA Profit: €163.16, Secondary Profit: €0.00, Total: €163.16
2024-12-24 → Secondary Reserve: 0%, DA Profit: €106.69, Secondary Profit: €0.00, Total: €106.69
2024-12-25 → Secondary Reserve: 70%, DA Profit: €26.70, Secondary Profit: €84.35, Total: €111.05
2024-12-26 → Secondary Reserve: 30%, DA Profit: €60.27, Secondary Profit: €21.05, Total: €81.32
2024-12-27 → Secondary Reserve: 30%, DA Profit: €52.27, Secondary Profit: €21.17, Total: €73.44
2024-12-28 → Secondary Reserve: 70%, DA Profit: €21.75, Secondary Profit: €78.40, Total: €100.15
2024-12-29 → Secondary Reserve: 0%, DA Profit: €73.79, Secondary Profit: €0.00, Total: €73.79
2024-12-30 → Secondary Reserve: 70%, DA Profit: €23.78, Secondary Profit: €114.56, Total: €138.34
2024-12-31 → Secondary Reserve: 30%, DA Profit: €46.74, Secondary Profit: €19.56, Total: €66.29
2024 Total: €49189.45
```

Figure 5.3: Example of results format (case: 1 MW, 2 MWh, DOD = 0.7)

Comparing the life cycle of the batteries with the life expectancy, several important observations emerge.

For the LFP battery, assuming one full charge-discharge cycle per day, as modeled in the simulation, at a DOD of 80%, the system will wear out in approximately 2,400 full cycles, meaning, in just over 6.5 years, which is significantly shorter, compared to its life expectancy. Beyond this point, the battery would no longer be capable of delivering 80% of its original capacity, necessitating a reduction in DOD to prolong usability. Interestingly, for the LFP system, reducing the DOD to 60% greatly extends the battery's cycle life. At this depth, the LFP battery is expected to perform up to 8,000 full cycles, which corresponds to nearly 22 years of operation, if the behavior is according to the conducted simulation [38]. It is possible to conclude that the relation between the DOD and life cycle is not linear, if it was, the life extension from reducing the DOD from 80% to 60% would result in a life cycle of approximately 4,000 cycles, or about 13 years. Instead, the battery achieves nearly double that, indicating diminishing degradation rates at lower DOD levels.

To maximize the investment return of the LFP BESS as quickly as possible, the operational strategy adopted relies on taking advantage of the 80% DOD as much as possible, meaning the 2400 cycles, followed by a transition to 60%, which, assuming that the degradation of the battery is linear for a given DOD, will still have available 4000 cycles, which will be enough to exceed the battery life's expectancy. To sum up, the conducted simulation for the LFP BESS will test the yearly turnover of each scenario for a DOD of 0.8 and 0.6.

In the VRFB case, given that the rated life cycle is 5,250 full cycles, VRFB systems are capable of operating well beyond the expected lifespan, assuming simulation operational conditions, without requiring a reduction in the DOD. It is considered a constant DOD of 80%.

The CAES system does not have a life cycle. Therefore, it only considered the system's life expectancy of 60 years with a DOD of 80% in the calculations.

In the following subsections, the results obtained from the most relevant simulations performed are presented. The data is structured to address different scenarios, with connection power ranging from 1 MW to 100 MW.

Comparisons of the different scenarios and quantitative findings are provided in a structured manner, with tables, graphs, and descriptive statistics used to highlight the main trends and observations. An in-depth interpretation of the results is provided in Section 5.4.

5.3.1 Connection Power of 1 MW

Table 5.3 presents the results for each evaluated scenario under a 1 MW connection capacity, along with the corresponding total revenue assuming the use of an LFP battery as the storage system.

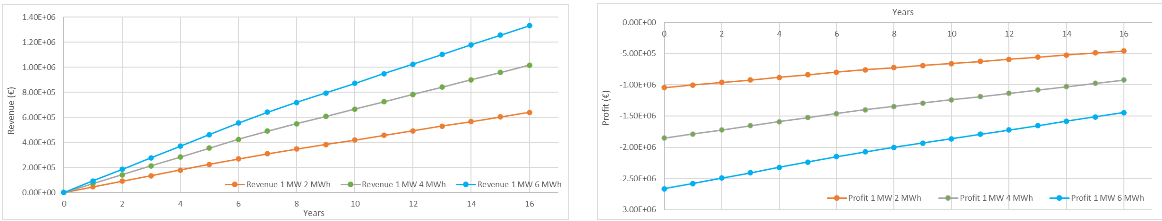
Table 5.3: Simulation results and respective revenue of an LFP BESS with a 1 MW connection capacity

Power (MW)	Capacity (MWh)	DOD	Yearly Turnover €	Life Cycle	Total Revenue k€
1	2	0.8	44605	6.57	639
		0.6	36711	16	
1	4	0.8	70784	6.57	1016
		0.6	58445	16	
1	6	0.8	92429	6.57	1332
		0.6	76811	16	

Where,

$$TotalRevenue = YearlyTurnover_{0.8} * LifeCycle_{0.8} + YearlyTurnover_{0.6} * (LifeCycle_{0.6} - LifeCycle_{0.8}) \tag{5.3}$$

Below, Figure 5.4 presents a graphical view of the revenue and profit of each scenario over the years the battery is operating.



(a) Evolution of revenue of a LFP BESS over time with a connection power of 1 MW, not considering costs

(b) Evolution of profit of a LFP BESS over time with a connection power of 1 MW, considering costs of acquisition and maintenance

Figure 5.4: Analysis of a LFP BESS with a connection power of 1 MW over time

From Figure 5.4, it is possible to conclude that none of the presented solutions are able to cover the entire investment. However, it is important to note that the 2 MWh solution presents the lowest gross loss of the simulated scenarios. The operational time required to break even can be calculated through the return on investment:

$$TBE = \frac{Investment_{total}}{Revenue_{yearly}} = \frac{AcquisitionCost + MaintenanceCost_{yearly} \cdot TBE}{Revenue_{yearly}} \tag{5.4}$$

Due to its nature, iterative methods, such as Newton-Raphson, are required to solve the TBE equation. However, since maintenance costs are typically significantly lower than acquisition costs, we adopted an approximation by considering the total maintenance costs over the system's life expectancy as part of the initial investment. Using this simplification in (5.4), we obtain the following values for TBE:

1 MW, 2 MWh scenario:

$$TBE = \frac{1096.9}{\frac{639}{16}} = 27.5 years \tag{5.5}$$

1 MW, 4 MWh scenario:

$$TBE = \frac{1939.8}{\frac{1016}{16}} = 30.5 years \tag{5.6}$$

1 MW, 6 MWh scenario:

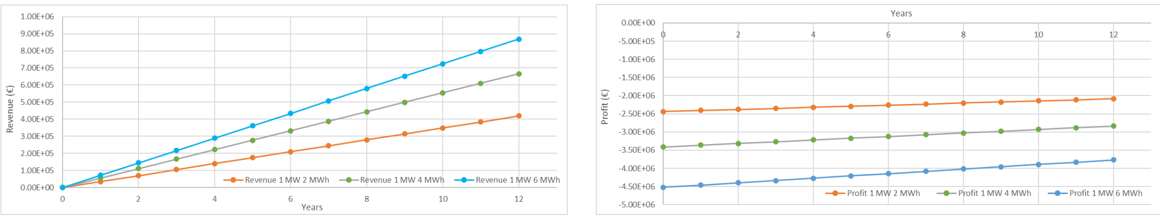
$$TBE = \frac{2776.0}{\frac{1332}{16}} = 33.4 years \tag{5.7}$$

Time to Break Even (TBE) is the amount of time an investment takes to break even, represented by the intersection of the profit graphic with the X axis. In this case, the DOD is adjusted during the battery's operational lifetime, so the yearly revenue used to calculate the TBE is the average revenue over the 16 years. Considering this adjustment, the TBE is 27.5, 30.5, and 33.4 years for the 2 MWh, 4 MWh, and 6 MWh scenarios, respectively. The results obtained require the battery to have a lifetime that surpasses the expected value provided by PNNL in every case, meaning that the investment is not profitable.

VRFB batteries have the potential to deliver improved performance due to their distinct characteristics, such as a significantly longer life cycle. This scenario results are expressed in Table 5.4 and illustrated in Figure 5.5.

Table 5.4: Simulation results and respective revenue of an VRFB BESS with a 1 MW connection capacity

Power (MW)	Capacity (MWh)	DOD	Yearly Turnover €	Life Cycle	Total Revenue k€
1	2	0.8	34932	12	419
1	4	0.8	55433	12	665
1	6	0.8	72384	12	869



(a) Evolution of revenue of a VRFB BESS over time with a connection power of 1 MW, not considering costs

(b) Evolution of profit of a VRFB BESS over time with a connection power of 1 MW, considering costs of acquisition and maintenance

Figure 5.5: Analysis of a VRFB BESS with a connection power of 1 MW over time

From Figure 5.5, it is possible to conclude that, like the LFP system, VRFB systems with this range of connection capacity are also unable to cover the entire investment.

1 MW, 2 MWh scenario:

$$TBE = \frac{2503.5}{34.9} = 71.7 years \tag{5.8}$$

1 MW, 4 MWh scenario:

$$TBE = \frac{3499.6}{55.4} = 63.1 years \tag{5.9}$$

1 MW, 6 MWh scenario:

$$TBE = \frac{4634.8}{72.4} = 64.0 years \tag{5.10}$$

For VRFB batteries, the TBE takes 71.7, 63.1, and 64 years for the 2 MWh, 4 MWh, and 6 MWh scenarios, respectively, demonstrating a performance far worse than the LFP battery. However, it is interesting to note that contrary to the previous case, VRFB batteries exhibit better results in the 4 MWh scenario than the 2 MWh scenario. This improvement is primarily attributed to acquisition costs, which scale more favorably with acquired capacity relative to LFP systems.

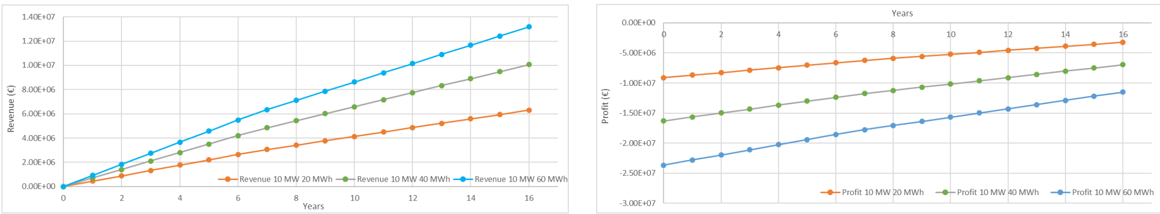
5.3.2 Connection Power of 10 MW

Table 5.5 presents the results for each evaluated scenario under a 10 MW connection capacity, along with the corresponding total revenue assuming the use of an LFP battery as the storage system.

Table 5.5: Simulation results and respective revenue of an LFP BESS with a 10 MW connection capacity

Power (MW)	Capacity (MWh)	DOD	Yearly Turnover €	Life Cycle	Total Revenue k€
10	20	0.8	440875	6.57	6309
		0.6	361878	16.00	
10	40	0.8	700972	6.57	10058
		0.6	578241	16.00	
10	60	0.8	915576	6.57	13185
		0.6	760285	16.00	

Below, Figure 5.6 presents a graphical view of the revenue and profit of each scenario over the years the LFP system is operating.



(a) Evolution of revenue of a LFP BESS over time with a connection power of 10 MW, not considering costs

(b) Evolution of profit of a LFP BESS over time with a connection power of 10 MW, considering costs of acquisition and maintenance

Figure 5.6: Analysis of a LFP BESS with a connection power of 10 MW over time

From Figure 5.6, it is possible to conclude that, like in previous cases, none of the presented solutions are able to cover the entire investment. The scenario that presents the best performance is still the one with a 2 to 1 capacity/power ratio:

10 MW, 20 MWh scenario:

$$TBE = \frac{9544}{\frac{6309}{16}} = 24.2 years \tag{5.11}$$

10 MW, 40 MWh scenario:

$$TBE = \frac{17027}{\frac{10058}{16}} = 27.1 years \tag{5.12}$$

10 MW, 60 MWh scenario:

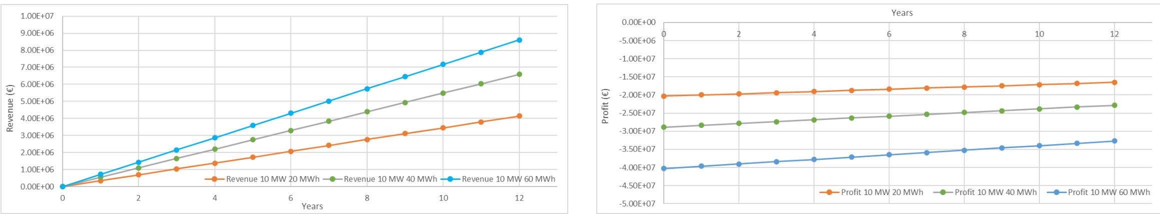
$$TBE = \frac{24687}{\frac{13185}{16}} = 30.0 years \tag{5.13}$$

For these scenarios, the TBE is 24.2, 27.1, and 30.0 years for the 20 MWh, 40 MWh, and 60 MWh scenarios, respectively. Despite the TBE still being above the operational life expectancy for this technology, the 10 MW, 20 MWh scenario presents the best overall results so far.

The VRFB BESS 10 MW scenario results are expressed in Table 5.6 and illustrated in Figure 5.7.

Table 5.6: Simulation results and respective revenue of an VRFB BESS with a 10 MW connection capacity

Power (MW)	Capacity (MWh)	DOD	Yearly Turnover €	Life Cycle	Total Revenue k€
10	20	0.8	345263	12	4143
10	40	0.8	548954	12	6587
10	60	0.8	717018	12	8604



(a) Evolution of revenue of a VRFB BESS over time with a connection power of 10 MW, not considering costs

(b) Evolution of profit of a VRFB BESS over time with a connection power of 10 MW, considering costs of acquisition and maintenance

Figure 5.7: Analysis of a VRFB BESS with a connection power of 10 MW over time

From Figure 5.7, it is possible to conclude that, like the previous solutions, these scenarios for the VRFB system are unable to cover the entire investment.

10 MW, 20 MWh scenario:

$$TBE = \frac{20652}{345} = 59.8 years \tag{5.14}$$

10 MW, 40 MWh scenario:

$$TBE = \frac{29416}{549} = 53.6 years \tag{5.15}$$

10 MW, 60 MWh scenario:

$$TBE = \frac{41309}{717} = 57.6 years \tag{5.16}$$

For VRFB BESS, the TBE takes 59.8, 53.6, and 57.6 years for the 20 MWh, 40 MWh, and 60 MWh scenarios, respectively, maintaining a significant profit gap when compared to the LFP BESS. Similarly to the LFP BESS, this scenario presents better results when compared to the same technology with a lower connection power. The best performing solution for this technology is the 10 MW, 40 MWh with an even larger difference from other solutions, compared to the previous case.

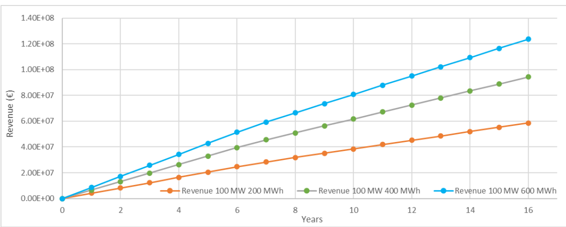
5.3.3 Connection Power of 100 MW

Table 5.7 presents the results for each evaluated scenario under a 100 MW connection capacity, along with the corresponding total revenue assuming the use of an LFP battery as the storage system.

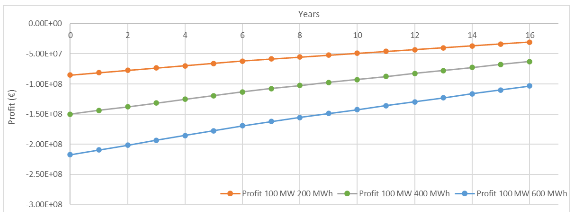
Table 5.7: Simulation results and respective revenue of an LFP BESS with a 100 MW connection capacity

Power (MW)	Capacity (MWh)	DOD	Yearly Turnover €	Life Cycle	Total Revenue k€
100	200	0.8	4102616	6.57	58637
		0.6	3359797	16	
100	400	0.8	6576356	6.57	94220
		0.6	5409687	16	
100	600	0.8	8568090	6.57	123600
		0.6	7137559	16	

Below, Figure 5.8 presents a graphical view of the revenue and profit of each scenario over the years the battery is operating.



(a) Evolution of revenue of a LFP BESS over time with a connection power of 100 MW, not considering costs



(b) Evolution of profit of a LFP BESS over time with a connection power of 100 MW, considering costs of acquisition and maintenance

Figure 5.8: Analysis of a LFP BESS with a connection power of 100 MW over time

From Figure 5.8, it is possible to conclude that, like in previous cases, none of the presented solutions are able to cover the entire investment. The scenario that presents the best performance is still the one with a 2 to 1 capacity/power ratio:

100 MW, 200 MWh scenario:

$$TBE = \frac{89227}{\frac{58637}{16}} = 24.3 years \tag{5.17}$$

100 MW, 400 MWh scenario:

$$TBE = \frac{156981}{\frac{94220}{16}} = 26.7 years \tag{5.18}$$

100 MW, 600 MWh scenario:

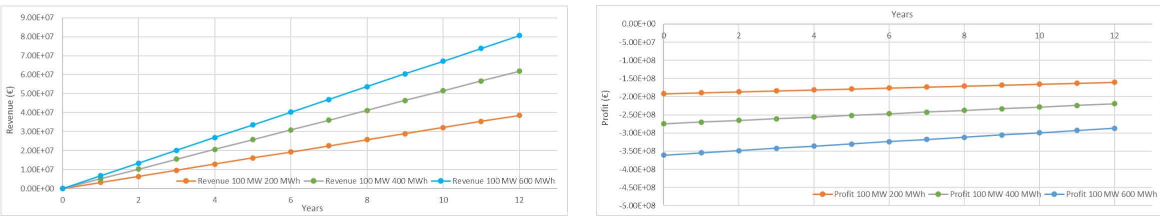
$$TBE = \frac{226942}{\frac{123600}{16}} = 29.4 years \tag{5.19}$$

For these scenarios, the TBE is 24.3, 26.7, and 29.4 years for the 200 MWh, 400 MWh, and 600 MWh scenarios, respectively. Despite the TBE still being above the operational life expectancy for this technology, the 100 MW, 200 MWh scenario presents the best results in this range of capacity, performing slightly worse than the previous case.

The VRFB BESS scenario results are expressed in Table 5.8 and illustrated in Figure 5.9.

Table 5.8: Simulation results and respective revenue of an VRFB BESS with a 100 MW connection capacity

Power (MW)	Capacity (MWh)	DOD	Yearly Turnover €	Life Cycle	Total Revenue k€
100	200	0.8	3212892	12	38555
100	400	0.8	5150158	12	61802
100	600	0.8	6709950	12	80519



(a) Evolution of revenue of a VRFB BESS over time with a connection power of 100 MW, not considering costs

(b) Evolution of profit of a VRFB BESS over time with a connection power of 100 MW, considering costs of acquisition and maintenance

Figure 5.9: Analysis of a VRFB BESS with a connection power of 100 MW over time

From Figure 5.9, it is possible to conclude that, like the previous solutions, this scenarios for the VRFB system are still unable to cover the entire investment.

100 MW, 200 MWh scenario:

$$TBE = \frac{198797}{3213} = 61.9 years \tag{5.20}$$

100 MW, 400 MWh scenario:

$$TBE = \frac{281001}{5150} = 54.6 years \tag{5.21}$$

100 MW, 600 MWh scenario:

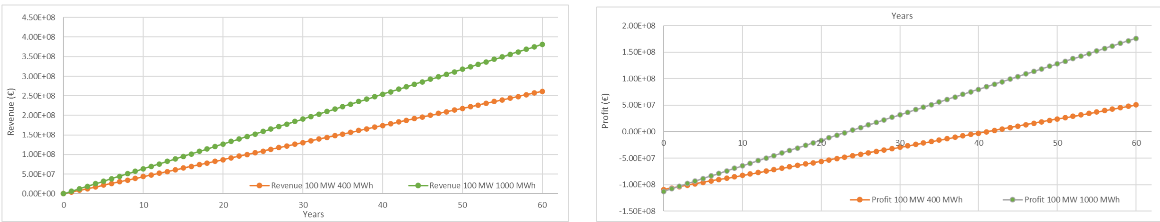
$$TBE = \frac{367379}{6710} = 54.8 years \tag{5.22}$$

For VRFB BESS, the TBE takes 40.2, 35.5, and 35.6 years for the 200 MWh, 400 MWh, and 600 MWh scenarios, respectively, maintaining the lower performance when compared to the LFP BESS. Similarly to the LFP BESS, this scenario presents slightly worse results than the previous case.

As mentioned in chapter 3, CAES systems are usually implemented at the grid-scale level. Accordingly, in this section this technology will be analyzed. The corresponding results are expressed in Table 5.9 and illustrated in Figure 5.10.

Table 5.9: Simulation results and respective revenue of an CAES system with a 100 MW connection capacity

Power (MW)	Capacity (MWh)	DOD	Yearly Turnover €	Life Cycle	Total Revenue k€
100	400	0.8	4357826	60	261470
100	1000	0.8	6354211	60	381253



(a) Evolution of revenue of a CAES system over time with a connection power of 100 MW, not considering costs

(b) Evolution of profit of a CAES system over time with a connection power of 100 MW, considering costs of acquisition and maintenance

Figure 5.10: Analysis of a CAES system with a connection power of 100 MW over time

From Figure 5.10, it is possible to conclude that the CAES system is profitable in both scenarios, at different points in time.

100 MW, 400 MWh scenario:

$$TBE = \frac{211144}{4358} = 48.5 years \tag{5.23}$$

100 MW, 1000 MWh scenario:

$$TBE = \frac{205113}{6354} = 32.3 years \tag{5.24}$$

In this case, the difference between the calculated TBE and the intersection with X axis observable in Figure 5.10 is relevant. This disparity is due to the implicit larger life expectancy of this technology. The TBE calculated iteratively approximates to the 42th year of operation for the 400 MWh scenario, and to the 24th year for the 1000 MWh scenario.

The total profits of the CAES system at the end of its expected lifespan (60 years) were calculated for each scenario using the expression (5.25).

$$Profit = \frac{Revenue_{total} - Investment_{total}}{Investment_{total}} \tag{5.25}$$

100 MW, 400 MWh scenario:

$$Profit = \frac{50326}{211144} = 23.8\% \tag{5.26}$$

100 MW, 1000 MWh scenario:

$$Profit = \frac{176140}{205113} = 85.9\% \tag{5.27}$$

In summary, the CAES system demonstrated the most favorable performance for the intended mode of operation, being the only economically viable option. It was followed by the LFP and VRFB systems.

5.4 Economical Analysis

In this chapter, the results obtained are processed and compared to facilitate analysis and decision making of potential investors.

The currency exchange is not performed in the analysis made in Chapter 5.3. The data provided by PNNL for the costs of storage systems is in US dollar, but the revenue from participating in the market is calculated in Euro. Although this adjustment would slightly improve results, it was decided not to consider it because of the complexity of evaluating the correct exchange rate since the system prices are relative to an average of 2023, and the dataset selected for operating in the market occurs in 2024.

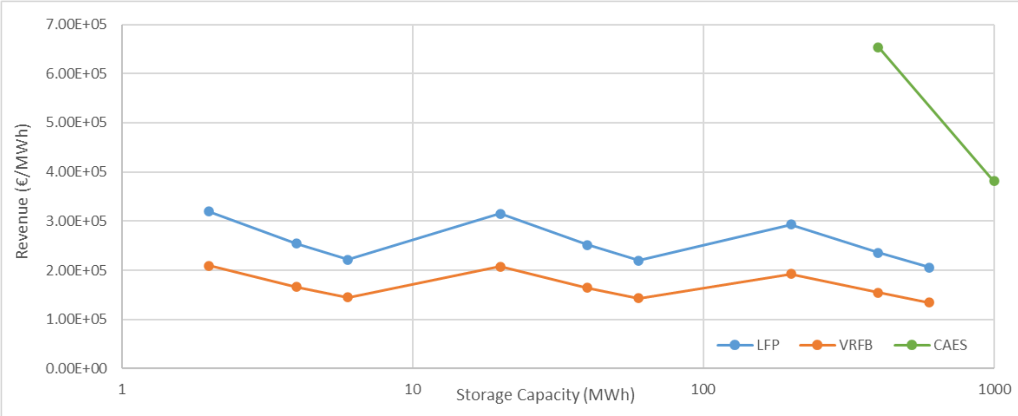


Figure 5.11: Variation of revenue per unit of installed capacity with increasing system size

The CAES system presents an unexpectedly sharp decrease in generated revenue compared to the other technologies in the 1000 MWh scenario, visible in Figure 5.11. This phenomenon highlights one of the program's limitations, particularly the necessity to use all of the system's capacity. In this scenario, the capacity to power ratio is so large, translating into low flexibility, at a point where, on certain days, the best solution is to not participate in the day-ahead market.

The main takeaways from Figure 5.11 are:

- Revenue tends to decrease with the increase of capacity to power ratio;
- Revenue tends to decrease with total installed capacity;

Two main reasons are responsible for these conclusions. Firstly, the larger the system's capacity, the greater impact it will have on the market prices, which means that although a certain technology might present a specific result for a particular scenario, as more investment is made in this field, the more stable the price will become, meaning that the methodology will shift to a majority of operation in the secondary regulation reserve market, and, for the current situation, the profit margins will lower. Secondly, as mentioned above, the flexibility of operation is key to increasing profit margins, meaning that the capacity to power ratio needs to be well balanced according to costs to reach the best possible solution.

The Pacific Northwest National Laboratory forecasted conservative, realistic and optimistic technical-economic metrics for the different storage technologies at 2030 [38]. Below, the LFP system is analyzed assuming the 2030 forecast, since it is the most promising battery system.

Table 5.10: Acquisition costs for LFP systems in 2023 and realistic projection for 2030 [38]

Power (MW)	1			10			100		
Capacity (MWh)	2	4	6	20	40	60	200	400	600
2023 ($/kW)	1040.88	1841.72	2648.46	904.44	1618.62	2350.83	846.01	1490.89	2158.16
2030 ($/kW)	838.89	1462.4	2096.32	720.86	1270.09	1833.26	674.77	1162.4	1671.64

According to PNNL, and based on Table 5.10, the average acquisition costs of LFP systems in 2030 is 78.9% of the same system in 2023. On top of that, the realistic scenario expects the system's efficiency to increase from 83% to 85% and the life cycle to improve significantly.

In the LFP system best case scenario calculated (10 MW, 20 MWh), the TBE was 24.2 years. Considering these adjustments, the total investment would be 7588k€ instead of 9544k€, and the revenue would totalize 6735k€ instead of 6309k€, resulting in:

$$TBE = \frac{7588}{\frac{6735}{16}} = 18.0 years \tag{5.28}$$

Considering the realistic characteristics forecast of the LFP system, it is not yet capable of fulfilling the investment made, although it presents a significantly improved result.

Considering the optimistic forecast, the TBE lowers below the 16 year operational lifespan turning the investment in the LFP technology to operate in the markets profitable:

$$TBE = \frac{6454}{\frac{7224}{16}} = 14.3 years \tag{5.29}$$

Chapter 6

Conclusion and Development Prospects

The shift of power systems toward sustainability and resilience is inseparable from the overall adoption of energy storage technologies. As this dissertation has shown, the strategic operation of storage devices in electricity markets, specifically the day-ahead and secondary regulation band markets, presents an opportunity to maximize both economic and system-wide benefits.

Through the development and application of a simulation tool, this work has demonstrated that storage systems are able to achieve economically viable outcomes under appropriate configurations and market conditions. The analysis reveals that participation in both markets requires careful orchestration of capacity allocation and charging/discharging strategies, as profitability is sensitive to market dynamics, storage technology characteristics, and system sizing.

The comparative study of storage technologies further emphasizes the importance of aligning technological capabilities with investment objectives. For instance, Compressed Air Energy Storage (CAES) systems emerged as the top-performing technology under the developed methodology and are particularly well-suited for large-scale, long-term deployments. In contrast, Lithium Iron Phosphate (LFP) batteries demonstrated the best performance among battery technologies, offering greater flexibility and better alignment with more restrictive financial and operational strategies. These insights are crucial for guiding investors and policymakers toward informed decisions.

However, the future profitability of such investments remains uncertain, as it depends on evolving electricity market dynamics, regulatory changes, fluctuations in storage prices, and the emergence of new technologies.

Future work should focus on enhancing the simulation tool to overcome its current limitations, therefore improving the accuracy of the results. Additionally, the analyses should be expanded to evaluate emerging storage technologies, such as sodium-ion batteries, and innovative concepts like the exploration of end-of-life batteries from electric vehicles. These innovations have the potential to significantly increase profitability and sustainability, offering new pathways for integrating flexible, cost-effective storage solutions into electricity markets.

In conclusion, this dissertation addresses storage devices' economic and operational promise in modern power systems and electricity markets. It lays a strong foundation for future exploration and highlights the need for continued innovation and regulatory support.

References

[1] Lessons from Liberalised Electricity Markets, 2005. Accessed: 30 out. 2024. URL: https://www.iea.org/reports/lessons-from-liberalised-electricity-markets.

[2] Hive Power. Grid stability issues with renewable energy sources: How they can be solved. 2021. Accessed: 22 dec. 2024. URL: https://www.hivepower.tech/blog/grid-stability-issues-with-renewable-energy-how-they-can-be-solved.

[3] Rafael Zárate-Miñano, Miguel Cañas-Carretón, and Miguel Carrión. Hybridization of existing solar pv farms considering wind power, batteries and electrolyzers. *International Journal of Electrical Power Energy Systems*, 155:109557, 2024. URL: https://www.sciencedirect.com/science/article/pii/S0142061523006142, doi:https://doi.org/10.1016/j.ijepes.2023.109557.

[4] REN Redes Energéticas Nacionais. Secondary capacity, 2021. Accessed: 23 dec. 2024. URL: https://mercado.ren.pt/EN/Electr/MarketInfo/SystemResults/SecReserveAllocation/Pages/default.aspx.

[5] José Pedro Duarte Moutinho Areosa. Estimativa do impacto de alterações nas ofertas de banda de regulação secundária no preço da banda em 2022. 2024.

[6] Saša Butorac. Eu electricity grids. *EPRS - European Parliamentary Research Service*, 2025. URL: https://www.europarl.europa.eu/RegData/etudes/BRIE/2025/772854/EPRS_BRI(2025)772854_EN.pdf.

[7] Gregor Erbach. *Understanding electricity markets in the EU*. European Parliamentary Research Service (EPRS), 2016. Acessed: 6 jan. 2025. URL: https://energy.mit.edu/research/future-of-energy-storage/.

[8] Rodrigo Miguel Batista Lousado. Avaliação da viabilidade económica da realização de arbitragem de preços utilizando dispositivos de armazenamento e valores dos preços de mercado de 2022. 2024.

[9] C. Monteiro, Ignacio Ramirez-Rosado, Luis Fernandez-Jimenez, and Pedro Conde. Short-term price forecasting models based on artificial neural networks for intraday sessions in the iberian electricity market. *Energies*, 9:721, 09 2016. doi:10.3390/en9090721.

[10] F.-Javier Heredia, Marcos J. Rider, and Cristina Corchero. Optimal bidding strategies for thermal and generic programming units in the day-ahead electricity market. *Power Systems, IEEE Transactions on*, 25:1504 – 1518, 09 2010. doi:10.1109/TPWRS.2009.2038269.

[11] DGEG Direção Geral de Energia e Geologia. Mercado intradiário, 2025. Accessed: 09 jun. 2025. URL: https://www.dgeg.gov.pt/pt/areas-transversais/mercados-e-mecanismos-de-capacidade/mibel/mercado-intradiario/.

[12] Eurostat. Electricity price statistics, 2024. Accessed: 10 jan. 2025. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Electricity_price_statistics.

[13] Eurostat. Natural gas price statistics, 2024. Accessed: 10 jan. 2025. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Natural_gas_price_statistics.

[14] Trading Economics. EU Carbon PermitsPrice. Accessed: 10 jan. 2025. URL: https://tradingeconomics.com/commodity/carbon.

[15] Brandon Vargas. Day-ahead and Intraday Electricity Markets, 2024. Accessed: 23 dec. 2024. URL: https://medium.com/%40brandonvar/day-ahead-and-intraday-electricity-markets-1eb121dcab47.

[16] J. T. Saraiva, J. L. Pereira da Silva, M. T. Ponce de Leão. Mercados de Electricidade - Regulação e Tarifação de Uso das Redes. *FEUPEdições*, 2002.

[17] ENTSO-E European Network of Transmission System Operators for Electricity. Frequency Containment Reserves, 2025. Accessed: 15 jun. 2025. URL: https://www.entsoe.eu/network_codes/eb/fcr/.

[18] ENTSO-E European Network of Transmission System Operators for Electricity. PICASSO, 2025. Accessed: 15 jun. 2025. URL: https://www.entsoe.eu/network_codes/eb/picasso/.

[19] ENTSO-E European Network of Transmission System Operators for Electricity. Manually Activated Reserves Initiative, 2025. Accessed: 15 jun. 2025. URL: https://www.entsoe.eu/network_codes/eb/mari/.

[20] ENTSO-E European Network of Transmission System Operators for Electricity. TERRE, 2025. Accessed: 15 jun. 2025. URL: https://www.entsoe.eu/network_codes/eb/terre/.

[21] Abhimanyu Kaushal and Dirk Van Hertem. An overview of ancillary services and hvdc systems in european context. *Energies*, 2019.

[22] Entidade Reguladora dos Serviços Energéticos (ERSE). *Manual de Procedimentos da Gestão Global do Sistema do Setor Elétrico*. ERSE, 2023. Acessed: 23 dec. 2024. URL: https://www.erse.pt/media/icspgymj/diretiva-13_2023-mpggs.pdf.

[23] Zhang T. Sun L. Zhao, Y. Energy storage for black start services: A review. *Energies*, 2022. URL: https://link.springer.com/article/10.1007/s12613-022-2445-0.

[24] ERSExplica. *INVESTIGATION INTO THE IBERIAN BLACKOUT OF 28 APRIL 2025*. ERSE, 2025. Acessed: 10 jun. 2025. URL: https://www.erse.pt/media/qovd5vgq/ersexplica25_vfinal-en.pdf.

[25] Annette Evans, Vladimir Strezov, and Tim J. Evans. Assessment of utility energy storage options for increased renewable energy penetration. *Renewable and Sustainable Energy Reviews*, 16(6):4141–4147, 2012. URL: https://www.sciencedirect.com/science/article/pii/S1364032112002316, doi:https://doi.org/10.1016/j.rser.2012.03.048.

[26] Benjamin Kroposki. Integrating high levels of variable renewable energy into electric power systems. *Journal of Modern Power Systems and Clean Energy*, 5(6):831–837, 2017. doi:10.1007/s40565-017-0339-3.

[27] João Tomé Saraiva. Basic concepts and available storage technologies. *Campus REN - aprender é evoluir*, 2025.

[28] MIT Energy Initiative. *The Future of Energy Storage*. MIT, June 2022. Acessed: 11 dec. 2024. URL: https://energy.mit.edu/research/future-of-energy-storage/.

[29] Hybrit. Hydrogen storage. Accessed: 16 jun. 2025. URL: https://www.hybritdevelopment.se/en/a-fossil-free-development/hydrogen-storage/.

[30] Kethaki Wickramaarachchi and Manickam Minakshi. Status on electrodeposited manganese dioxide and biowaste carbon for hybrid capacitors: The case of high-quality oxide composites, mechanisms, and prospects. *Journal of Energy Storage*, 56:106099, 2022. URL: https://www.sciencedirect.com/science/article/pii/S2352152X22020874, doi:https://doi.org/10.1016/j.est.2022.106099.

[31] Hornsdale Power Reserve. Accessed: 16 jun. 2025. URL: https://hornsdalepowerreserve.com.au/.

[32] ARENA Australian Renewable Energy Agency. South Australian battery grows bigger and better, 2025. Accessed: 16 jun. 2025. URL: https://arena.gov.au/blog/south-australian-battery-grows-bigger-and-better/.

[33] Laijun Chen, Tianwen Zheng, Shengwei Mei, Xiaodai Xue, Binhui Liu, and Qiang Lu. Review and prospect of compressed air energy storage system. *Journal of Modern Power Systems and Clean Energy*, 2016.

[34] Chinese Academy of Sciences. World's First 100-MW Advanced Compressed Air Energy Storage Plant Connected to Grid for Power Generation, 2025. Accessed: 16 jun. 2025. URL: https://english.cas.cn/newsroom/research_news/phys/202209/t20220930_321008.shtml.

[35] Xavier Granados. Superconducting magnetic energy storage. *EERA Joint Program SP5*, 2019. URL: https://www.eera-energystorage.eu/component/attachments/?task=download&id=566:EERA_JPES_SP5_Factsheet_final.

[36] Nikolay Rogalev, Andrey Rogalev, Vladimir Kindra, Vladimir Naumov, and Igor Maksimov. Comparative analysis of energy storage methods for energy systems and complexes. *Energies*, 15:9541, 12 2022. doi:10.3390/en15249541.

[37] Polo Español S.A. (OMIE) OMI. Accessed: 17 mar. 2025. URL: https://www.omie.es/pt/file-access-list.

[38] Pacific Northwest National Laboratory. Accessed: 13 apr. 2025. URL: https://www.pnnl.gov/projects/esgc-cost-performance.

[39] Solomon Evro, Abdurahman Ajumobi, Darrell Mayon, and Olusegun Stanley Tomomewo. Navigating battery choices: A comparative study of lithium iron phosphate and nickel manganese cobalt battery technologies. *Future Batteries*, 4:100007, 2024. URL: https://www.sciencedirect.com/science/article/pii/S2950264024000078, doi:https://doi.org/10.1016/j.fub.2024.100007.