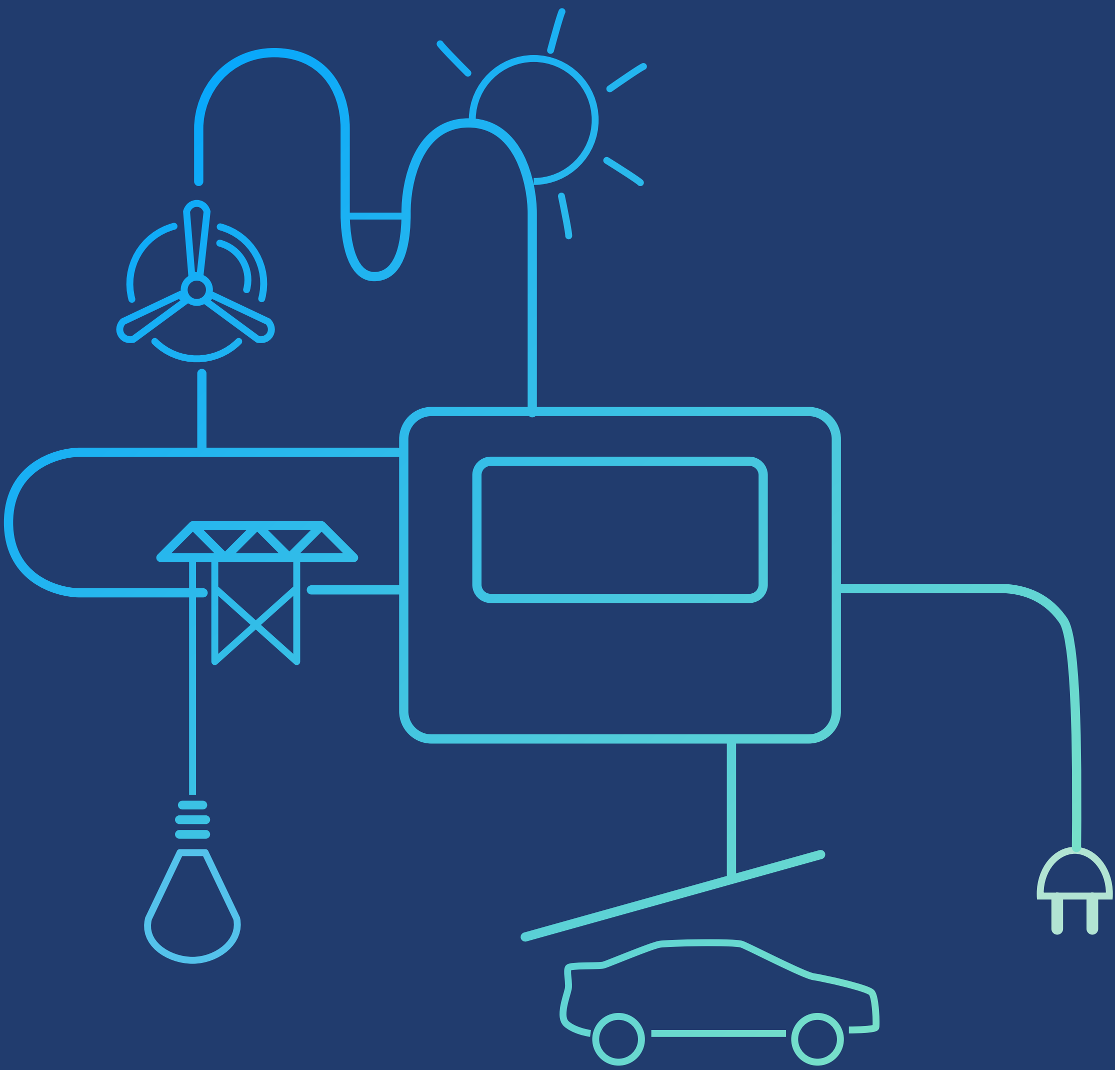
Delft University of Technology

Optimization of Battery Energy Storage System Operation in Distribution Grids



Delft University of Technology

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Challenge the future

Optimization of Battery Energy Storage System Operation in Distribution Grids

by

Luca Argiolas

to obtain the degree of Master of Science in Sustainable Energy Technology

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Abstract

The increment of Renewable Energy Sources (RES) and circulating Electric Vehicles (EVs) have brought new challenges in distribution networks due to their non-controllable characteristics. These assets increase the difficulties for Distribution System Operators (DSOs) to guarantee a safe and reliable operation. Battery Energy Storage Systems (BESSs) are currently seen as promising devices in future distribution grids. They can be deployed for several purposes, such as enhancing the grid capacity in hosting renewable generators and firming unpredictable EV charging while performing Energy arbitrage by buying and selling energy in the wholesale market (DAM). However, despite the standardized market product and its significant liquidity given by market coupling, European wholesale market prices might not be high enough to deem energy arbitrage as the only revenue stream since almost all types of energy generators have a lower cost than BESS. Currently, remunerated grid services such as primary frequency regulation (FCR) are the most valuable market for BESS in Europe. Nevertheless, the introduction of a notorious amount of BESS is congesting the markets and lowering the prices, as seen in UK and Germany. Consequently, at this stage, the high initial investment cost and the uncertain revenue streams challenge the spread of such technology. Therefore, this research aims to evaluate the potential business case for BESS in Distribution Networks (DNs) by integrating market application and additional DSO services. The technical and economic feasibility of the solution is verified via a case study.

First, a mathematical deterministic optimization problem is formulated using mixed integer linear programming (MILP). It integrates BESS operation in the DAM and FCR market. On top of these two revenues streams, remunerated services are being offered to the DSO and modeled in the algorithm. An already existing Photovoltaic (PV) - Fast Charging (FC) station environment is selected and cast in the research to shape such operations. Three players are involved, namely PV-FC station owner, DSO, and BESS owner.

The study shows that a potential BESS implementation in DNs is economically and technically advantageous for all the players implicated in the case study. In order to evaluate the current state of revenues, day-ahead and market prices Netherlands data of 2020 are employed, and a price-driven hybrid forecasting method has been proposed to determine future spot market prices. Yearly cash flows are eventually evaluated for the BESS owner. The results denote a positive NPV of 125 thousand euros and a payback time of around 3 years. By stacking extra revenues coming from DSO offered services, the payback could be reduced below 3 years whether higher speculation is executed on the remuneration agreement described in this thesis. Economically speaking, no assessment is outlined for the DSO. It is known from the literature that fees have to be paid in case congestion occurs on the line, however, the lack of data did not make such investigation possible. Its benefit relies on the technical aid that the BESS could provide by waiving the grid from peaks of power. Finally, economic benefits for the PV-FC station owner are also estimated. The owner would benefit from an overall 30% tariff reduction thanks to the peak shaving performed by the BESS.

Simulations attest that the main drawback lies in BESS capacity fading. State-of-the-art models equations are used to assess battery cell degradation, whereas the power electronics components wear is left out of the scope of this research. Due to the extensive number of applications and low BESS idling time, hard cycling leads to a shorter lifetime of fewer than 5 years. Hence, a limitation on the range of operation is essential. Narrowing SoC boundaries, BESS capacity fading improves newly to more than 5 years. On the other hand, the payback time shifts to above 3 years due to the restricted operation span.

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List of Abbreviations

AC	Alternating current
$BESS$	Battery Energy Storage System
BMS	Battery Management System
BTM	Behind the Meter
C_{ramp}	Ramp cost
C_t	Cash Flow at year t
$C\&I$	Commercial and Industrial
$CAPEX$	Capital Expenditures
DAM	Day-Ahead Market
DC	Direct Current
DoC	Depth of Charge
DoD	Depth of Discharge
DN	Distribution Network
DS	Distribution System
E^*	Battery Nameplate Capacity
EMS	Energy Management System
EoL	Battery End of Life
ESS	Energy Storage System
FC	Fast Charging
FCR	Frequency Containment Reserve
FTM	Front of the Meter
IRR	Internal Rate of Return
$LCOE$	Levelized Cost of Energy
LV	Low Voltage
$MILP$	Mixed Integer Linear Programming
MV	Medium Voltage
NPV	Net Present Value
$n_{max-FCR-cycles}$	Max Number of battery cycles performing FCR
$n_{max-cycles}$	Max Number of battery cycles occurred
P_{block}	Power blocked by DSo operation

P_{ch}	Battery charging power DC
P_{ch}^{*}	Battery rated charging power
P_{disch}	Battery discharging power DC
P_{disch}^{*}	Battery rated discharging ower
$P_{fcr_{bid-up}}$	FCR bid up
$P_{fcr_{bid-down}}$	FCR bid down
PFR	Primary Frequency Regulation
PV	Photovoltaic
RES	Renewable Energy Source
s_{cycles}	Slack variable indicating number of BESS cycles
SoC	Battery State of Charge
SoC_{block}	State of Charge blocked by DSo operation
t	Simulation timestep
V	Voltage
z	Primary Frequency Regulation timestep

Greek Symbols

β	Minimum Bid FCR
Γ	FCR min duration requirement
γ_{fcr}	Binary variable FCR bid activation
δ_{batt}	Binary variable charging/discharging activation
η_{rte}	Round trip efficiency
η_{ch}	Charging efficiency
η_{disch}	Discharging efficiency
λ	Day-ahead market price
λ_{fcr}	Primary frequency regulation market price
$\overline{\lambda_i^{FCR}}$	Month's average FCR price
σ	Standard deviation

1 Introduction

This first chapter introduces the problem studied in this thesis. The first part addresses the context and the motivation of the project and its relevance from a theoretical and practical perspective. It follows with the research question and concludes with the report outline.

1.1. Context and Motivation

The attention devoted to the energy sector by political decision-makers, technologists, and the public has been increasing for years and will probably reach new heights in the future. At the same time, the energy sector has undergone significant changes, and dramatic shifts in its structure are expected in the coming decades.

The first reason that has put the energy sector under the spotlight is the impact on the environment. Two orders of issues can be identified: those on the global scale and those with local implications; besides, the line between these two areas is sometimes blurry. The major global issue from an environmental perspective is global warming. Its relevance has attracted worldwide attention on how Greenhouse gas emissions (GHG) related to the energy sector, among others, is affecting our planet. Actions have been taken on the local, national, and global levels to curb GHG emissions and reduce the dependency on the energy sector from fossil fuels. At the same time, international agreements are eventually taking shape, intending to increase in the coming years. The Paris Agreement reached during the 2015 United Nations Climate Change Conference (COP21) is the 21^{st} internationally recognized treaty to set out a plan for emissions reductions and provide targets for the global temperature increase. As a consequence energy sector has received a strong push in the development. It is here worth mentioning how the massive development of sustainable technologies has drastically reduced their prices. For instance, China, in few years, has become the undisputed leader in the manufacturing of PV panels, dramatically reducing international prices and bringing these technologies close to grid parity in many areas [1].

Achieving the overall goals of the Paris Agreement will require a profound reduction in global greenhouse gas emissions, ideally by around 40%–50% by 2030 [2]. According to several studies coordinated by researchers from the Netherlands Environmental Assessment Agency and Utrecht University, current climate actions on national levels are insufficient to achieve the Paris goals of leading reduction in emissions by 2030 to 5.5% [3]. A substantial increase in both ambition and implementation is thus needed to achieve such a target. Furthermore, with the steady improvement of the worldwide quality of life, the electricity demand is increasing in all countries around the globe.

However, technical literature states that running 100% fossil-free by tomorrow is unreasonable, yet a transitional period is necessary to bridge the gap. Technologies and methods are needed to facilitate this evolution. Complex solutions are currently being developed, and energy storage has expressed great potential in easing the deployment of sustainable assets. As assessed by [4], Energy Storage Systems (ESSs) are expected to contribute to grid reliability assisting the integration of Renewable Energy Sources (RES) into existing grids, and, at the same time, driving the implementation of such systems in areas where electric grids do not exist yet through the creation of micro-grids. As a technology that integrates the capabilities of variable renewable energy resources into the electric grid, the applications of stationary ESS for power systems have recently been of significant importance. ESSs can become a vital part of investments in grid modernization to satisfy future demands under low carbon emissions constraints [5].

Among the ESS technologies, battery energy storage system (BESS) in the EMEA (Europe, Middle East, and Africa) market region has been experiencing intensive growth, and more and more opportunities are opening up for the companies to explore. BESS use cases cover a large scale of applications from low voltage (LV) to high voltage (HV) levels, including grid-tied and off-grid utilization. These applications are, for example, grid services, power quality, wholesale market participation, and transmission congestion relief. The synergies and contrasts between the different applications have been explored in the literature. Application stacking has been proven essential for an overall revenue increase concerning the provision of the single service separately [6] [7]. Addressing and combining multiple services from the technical, economic, and regulatory points of view is currently under investigation. Also, it is found that the chances for a positive business case increase through the involvement of several stakeholders.

At a Distribution System (DS) level, ESS devices relieve some current and future challenges, such as peak demand, line congestion, and integration of RES. By increasing the efficiency and security of electric grids, BESS will reduce energy production and delivery costs. However, BESS type and size are not clear yet to many stakeholders. Moreover, grid operators are still developing strategies and policies to control ESS and maximizing the value of this new technology [8].

1.2. Research Objectives

From the literature, it is clear that BESS is likely to become a necessary part of the future power grid. They have been identified as a feasible solution for reducing the peak power demand and smoothing variable load in distribution networks. The main topic of the work will concern the assessment of the potential revenues of operating a BESS in distinct wholesale and ancillary service markets, adding the DSO functionalities as an extra revenue stream. Using batteries in lucrative bidding strategies on the day-ahead markets combined with primary frequency service at the DS level has not yet been subjected to clear investigation.

1.2.1. Methodology

First, the literature review is performed about BESS technologies, application, electricity market, optimization for the energy system, and battery capacity fading. Secondly, a discrete optimization model has been developed to assess the performance of a BESS operating in distribution networks and performing energy arbitrage and primary frequency regulation. The optimization model was implemented in Pyomo, a python based library. The thesis follows with the validation of the optimization framework through case studies. Initially, a detailed analysis of the two is outlined, and a price forecasting framework is developed. To conclude, case studies results are evaluated in economic parameters, and the

BESS performance is assessed.

1.2.2. Research Questions

The following research objectives serve as a guideline for the thesis. *Are BESS a possible profitable asset in the current energy transition phase? Furthermore, what is the business case for BESS at distribution system level?*
The above question is the starting point of the following report. Storage systems can be very beneficial, but it is important to understand the needed revenue streams that allow the economic feasibility of energy storage projects. In order to facilitate answering the main question, several relevant sub-questions are also researched and evaluated:

- What are the set of functionalities to be performed by the BESS and the revenues streams at DS level?
- How can be modeled the BESS market participation and DSO operations in an optimization problem?
- How much is a RES owner saving from the grid connection thanks to the storage system? Moreover, what are the DSO benefits and the BESS owner's total remuneration?
- How can the lifetime of the battery system be evaluated?

1.3. Thesis Outline

The thesis is structured as follows.

Chapter 1: Introduction

This chapter gives a brief introduction to the current situation of storage technology. Secondly, the thesis motivation and the research questions for this thesis are defined.

Chapter 2: Literature Review

This second chapter contains the literature review on the knowledge required to perform this research. An extensive literature study is conducted on battery storage technology, electricity markets, and the optimization methodology regarding storage system operation in the current grids.

Chapter 3: Design Model Formulation

In chapter 3 the Python-based optimization model is illustrated.The objective functions and design constraints are outlined. In the end, the way how the algorithm works is illustrated.

Chapter 4: Case Study Analysis

The optimization has been assessed through case studies. The first one concerns BESS operation in electricity markets receiving remuneration by performing energy arbitrage and primary frequency regulation. While the second case study analyzes the benefit of BESS in distribution grids using a solar plant and a charging station environment as a reference. A price generation framework is also included in order to evaluate the future revenues for the system.

Chapter 5: Case Study Results

In this chapter, the outcome of the case studies is illustrated in terms of financial and technical benefits for the players involved in each case study. A solution is also proposed that optimizes BESS operations and the lifetime.

Chapter 6: Conclusion

The last chapter concludes the thesis, providing answers to the research questions, summarizing the main contributions, and giving recommendations on further research in this domain.

2

Literature Review

The development described in this thesis might be hard to understand due to the innovative field of application of the technology itself. This chapter aims to answer the first group of research questions employing the following sub-questions:

- *Why BESSs are different from other sustainable energy sources?*
- *What are the set of functionalities to be performed by the BESS?*
- *Which are the market in which such technology can be profitable?*
- *How can the optimization problem be formulated?*
- *What does it affect the battery capacity fading?*

Hence, first, it will be given a technical background of ESS with a particular focus on electrochemical type. Then, the major technical aspect that made possible its development in the market will be briefly discussed as well as the advantages and disadvantages of the options. In the third place, an overview of the possible market application and the integration into distribution networks (DN) will be investigated. To conclude, the different optimization methods applied in the literature will be presented.

2.1. The Energy Storage Technologies

Achieving the required balance between energy production and consumption has always been a challenge, but with the recent significant uptake of renewable generation, the uncertainties and the risks of reduced resilience of the power grid are higher than ever. Energy storage technologies can facilitate bridging the gap between the power demand and the power supplied and contribute to reliability on a long-term basis. With the integration of energy storage systems, the power and the energy challenges that conventional systems can face can be effectively confronted [9].

Even though there is a large variety of energy storage technologies, each storage system performs differently. Thus, different technologies tend to be utilized either for higher power with short durability or vice versa. Storage technologies can be categorized based on the principle of storing energy, such as mechanical, electromagnetic, or electrochemical storage, or by duration, with short, medium, or long term time scales [10].

It is out of the scope of this work to give an extensive presentation of each technology, while a more detailed overview of battery technologies will be presented in the following section. In the following pictures, it is relevant to comprehend the current situation in literature for battery technology and where the Li-Ion battery is allocated in terms of chemical characteristics, power ratings, and costs.

2.1.1. Battery Energy Storage Technology

This section will give a first overview of the battery storage technologies, and a second one is more oriented on the different Lithium-Ion technologies available in the European market. As outlined earlier, there are no perfect energy storage devices, which perform ideally when considering factors, such as specific energy, specific power, affordability, and safety. For instance, the discharge/charge rates are slower in batteries than in flywheels. Indeed, the batteries' storage principle is based on electrochemical charge and discharge reactions between a positive electrode (cathode) and a negative electrode (anode). The electrodes are separated by porous polymeric materials, which allow electrons and ions owing between each other and are immersed in an electrolyte [11]. Research has been ongoing for different types of chemical energy storage technologies, and the leading electrochemical technologies used in grid applications are Nickel-cadmium batteries, Sodium-sulfur batteries, Flow batteries, Lead-acid, and Lithium-ion batteries. Grid-connected electrochemical storage is characterized in terms of energy density, efficiency, lifetime, and costs, as illustrated in Figure 2.1.

Lead Acid is the most mature technology with the lowest price in the market. The main drawback concerns the very limited cyclability (250 cycles). NaS batteries are characterized by high energy density and long cycling life (up to 4500 cycles). The way Redox Flow batteries (RFB) are built provides flexibility in their design and operation. For instance, they are not subject to limitations in terms of reactants' lifetime (beyond 10000 cycles) and depth of discharge [12]. Despite the low energy density, they are granted as a promising candidate for grid-scale applications due to their economic performance. In particular, the ZEBRA batteries (composed of Vanadium and Zn-Br) are the most prominent ones.

With lithium-ion (Li-ion) battery technologies driving the market for portable electronic devices and tools for decades, the research has significantly pulled towards higher efficiencies and lower prices. This resulted in lithium-ion batteries gaining presence in distinct areas, such as in large-scale grid solutions. A Bloomberg New Energy Finance analysis of 2019 [1] reports that the cost of electricity from lithium-ion batteries has dropped by 76 % since 2012, making them close to competitive with the peaking power plants that are utilized during high demand times [14]. Consequently, with a constant decrease of their total cost of ownership (TCO), Li-ion battery storage systems could further establish themselves in the electricity sector. Moreover, on top of the good price tendencies, Li-ion batteries have several attractive characteristics. They present high energy density (90–190 Wh/kg)), as shown in figure 2.1, lightweight, high open-circuit cell voltage and high round-trip efficiency (around 85- 95%), safety, long cyclability (from 1,000 up to 10,000), low self-discharge rate (max 10 % per month) and low maintenance [13]. According to the European Commission, targets for Li-ion batteries include the achievement of an energy density up to 350 Wh/kg and specific power of 5 kW/kg within the next decade [15]. Drawbacks of the technology are the high capital cost, the limited availability of material, the possibility of thermal runaway, and safety issues, which require an advanced Battery Management System (BMS) [15]. Furthermore, the lifetime of Li-ion batteries is around 5–15 years, and the time of discharge varies from minutes to hours [13].

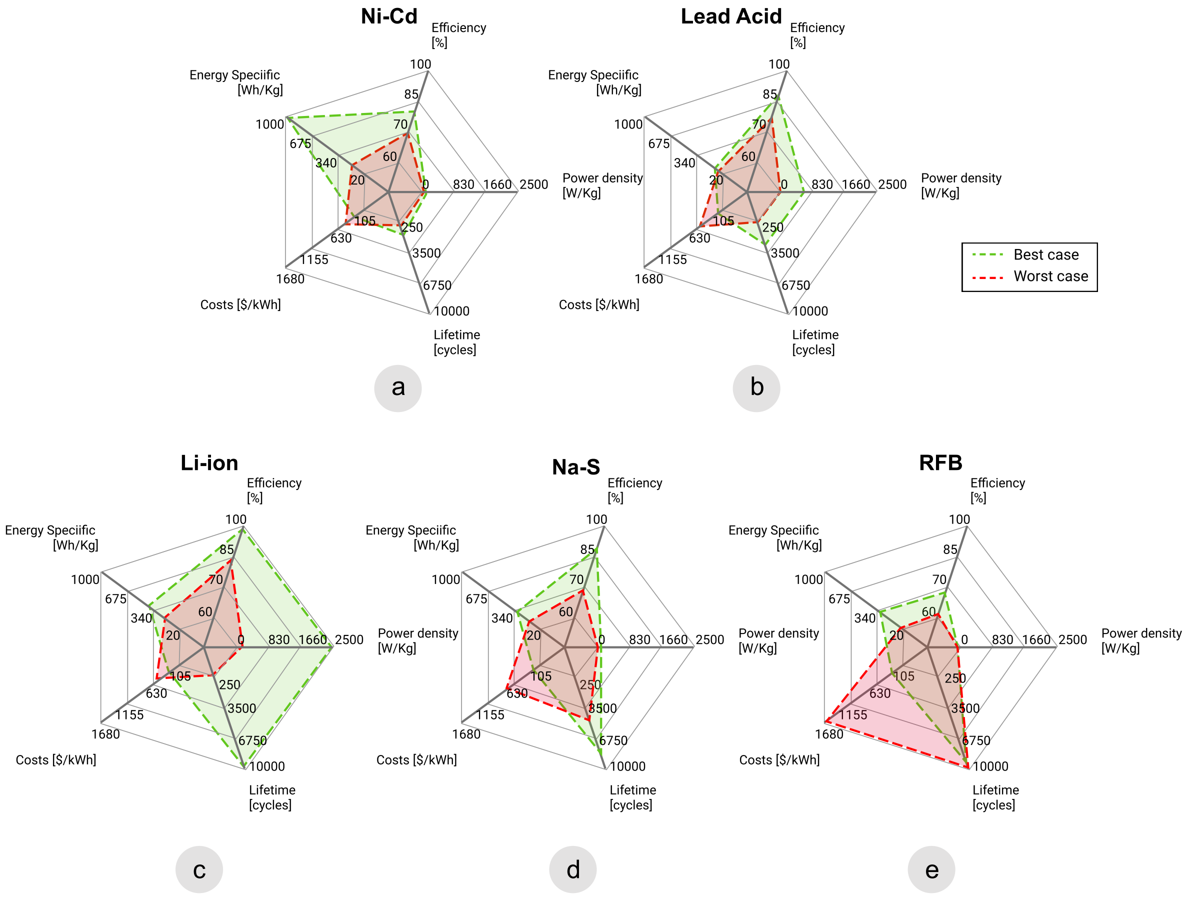


Figure 2.1: Comparison of power density, energy density, efficiency, costs and lifetime for the most popular battery storage technologies: (a) Nickel–Cadmium, (b) Lead Acid, (c)Lithium ion, (d) Sodium Sulfur and (e) Flow Battery - author's elaboration from [12] and [13]

There are various materials used for cathodes, and that material determines the features of the battery. The most mature configurations of Li-ion batteries and their main application areas are listed below [12]:

- Lithium Cobalt Oxide (LCO): *Portable electronic devices*
- Lithium Manganese Oxide (LMO): *Medical equipment*
- Lithium Iron Phosphate (LFP): *Electric vehicles, Grid applications*
- Lithium Nickel Manganese Cobalt Oxide (NMC): *Power tools, Electric vehicles, Grid applications*
- Lithium Nickel Cobalt Aluminum Oxide (NCA): *Electric vehicles, Grid applications.*

LCO based Li-ion battery cells use the first widely commercialized cathode material and have gained territory in the mobile phone and laptop industry. Although they are by far the most mature technology, they show a disadvantageous short life span and low thermal stability, which is otherwise a critical, pivotal point in favor for grid storage use-cases, in addition to cobalt becoming a scarce resource and thus, manufacturers tend to avoid the material [13]. As seen from Figure 2.2, the last three, LFP, NMC, and NCA, are the leading technologies that are utilized in grid applications because of three key advantages: high specific energy/power density, durability and wide availability of material [15]. Among the considered electrochemical compositions, the NMC offers the best performances leading it as the

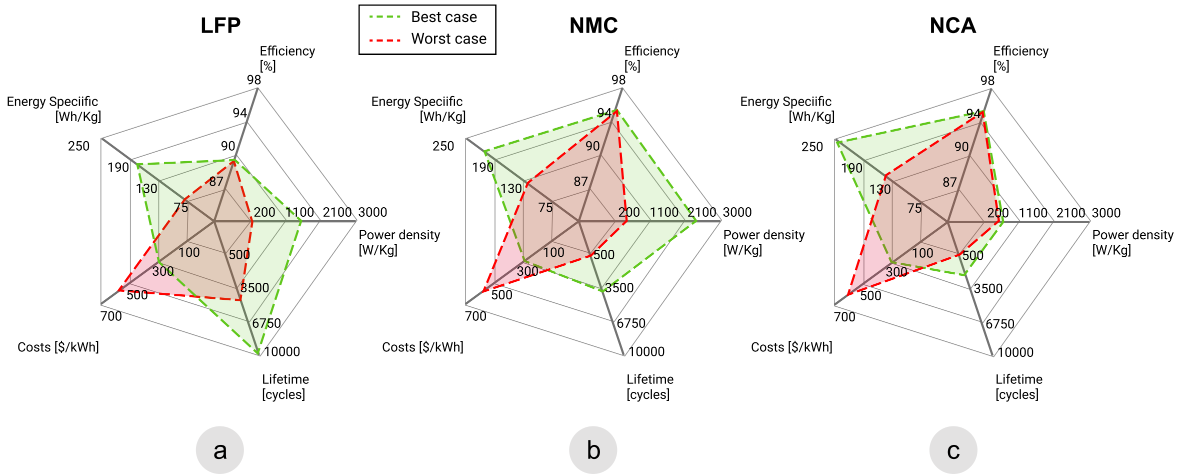


Figure 2.2: Comparison of power density, energy density, efficiency, costs and lifetime for the most popular Li-ion battery storage technologies for Grid applications: (a) Lithium Iron Phosphate, (b) Lithium Nickel Manganese Cobalt Oxide, (c)Lithium Nickel Cobalt Aluminum Oxide - author's elaboration from [12] and [13]

primary Li-ion technology stationary storage as well as electric vehicles [15]. On the other end, they have a shorter lifetime in comparison to the Lithium Iron Phosphate category. Furthermore, companies take severe measures towards battery recycling since Lithium-ion batteries contain valuable materials that can be recovered and recycled for further use in many other applications.

2.1.2. Typical BESS Set-up

The setup of a BESS is usually composed of several subsystems. An indicative layout is given in Figure 2.3. The core of the BESS is made up of the battery packs, which in turn are composed of the battery cells set up at the same voltage level. Regarding land usage, as said, Li-ion batteries are favorable compared to other battery technologies, since it has good energy and power density qualities. Moreover, more and more companies are going towards a novel and integrated product where the battery, including all auxiliary systems, is found within the product, designed to have the lowest impact on the external environment possible. The Heating, ventilation and air conditioning (HVAC) system maintains the packs within the operational temperature range. Indeed, BESSs are generally deployed in containers equipped with air conditioning systems, used to control the temperature of the battery cells. Mostly, the temperature is kept stable at $25°C$, to ensure optimal performances and extended lifetime [16]. The software component is the Battery Management System (BMS), which controls the battery operations such as charge/discharge rate (C-rate), State of Charge (SoC) management, and internal power electronics components as the DC-DC converters [17]. It provides the inputs to the Energy Management System (EMS), which coordinates the actual condition of the battery packs with several external inputs coming from aggregates BESS or grid operators.

The connection of the BESS to the AC distribution grid is made through power electronics-based converters. A transformer is commonly used to set up the voltage connection since, generally, the point of connection (POC) is at medium voltage (MV) or high voltage (HV). In some particular cases, the inverter is already included in the BESS side, this results in an easier coupling [17]. The grid interface refers to all the distribution and transmission systems as well as the energy generation sources and loads.

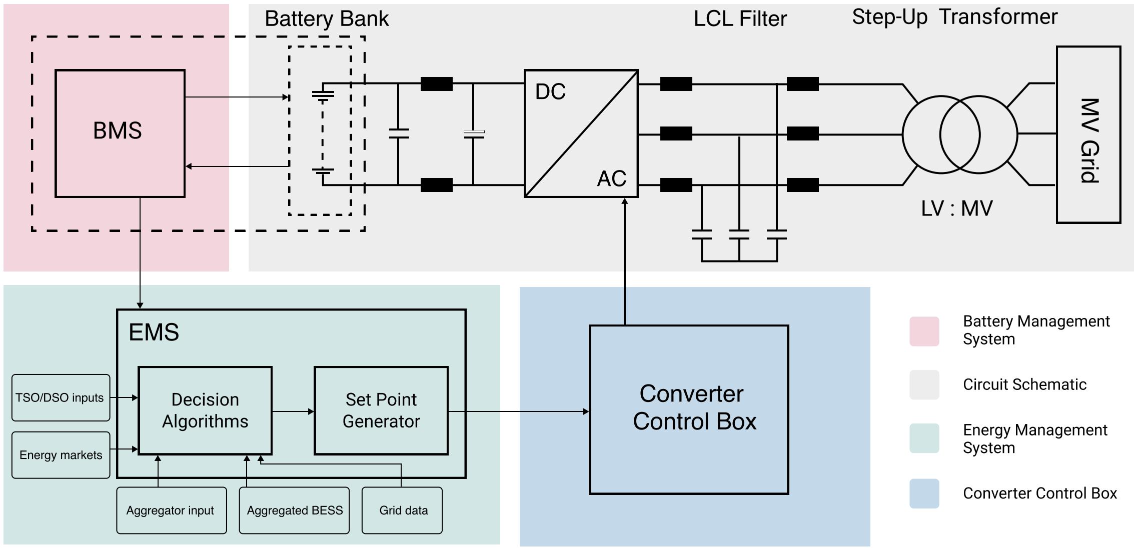


Figure 2.3: Circuit schematic of a grid-connected battery energy storage system with main components

2.2. Potential BESS Applications in Europe

According to the literature studies, there are several application options for battery storage systems. Each application can be categorized by its economic value source within three use cases: front-of-the-meter (FTM), behind-the-meter (BTM), and microgrid cases. These are gathered in Table 2.1

All grid services, wholesale market participation, renewable integration, transmission, and distribution system aids are included in the large group of FTM applications. The grid services consist of ancillary services, such as primary, secondary, tertiary reserve, power quality, and black start. With storage systems, revenue can be generated on the wholesale market, as well, by bidding on the day-ahead or the intraday market. Storage, moreover, facilitates renewables integration by ensuring ramp control of the renewable power plant and correcting forecast errors, which prevents paying penalty costs for the renewable plant. Another benefit of storage technologies is supporting transmission and distribution systems, providing congestion relief or peak shaving.

BTM applications are focus on Commercial & Industrial (C&I) utilization and aggregation projects. In C&I cases, the increase of renewable self-consumption and tariff optimization contributes to revenue generation. Meanwhile, Uninterruptible Power Supply (UPS) and backup power applications aim to ensure reliable power availability.

Microgrids' energy storage can enable extensive renewable penetration, thereby reducing energy costs (measured by the LCOE). Moreover, it can contribute to diesel abatement. In the case of an unreliable grid connection, storage solutions can serve as a backup. The island structures combined with full electro-mobility implementation and Renewable Energy Source (RES) development and storage systems are the most promising scenario for a complete change from fossil fuels to 100 % of clean energy yield [18].

However, specific existing conditions in particular areas and countries are making the BESS implementation and its following economic feasibility mainly focusing on a limited number of combined use-cases to increase the profitability rather than a single application[15]. As mentioned in section 2.1, Li-Ion batteries are still an expensive technology that requires elevated income sources on top of added non-monetized value to justify their implementation. Currently, the main use-cases in Europe still need to come to light. Moreover, BESS is not a mature technology widely implemented in Europe compared to the United States (US) [19]. In Figure 2.4 several countries categorized per use case are displayed.

Table 2.1: Potential Applications of Large Scale Li-Ion BESS - author's elaboration from [19] [15] [9]

Use Case	Category	Specific application
FTM	Grid Ancillary Services	Spinning Reserve/Fast Regulation Primary Frequency Regulation Secondary Frequency Regulation Tertiary Frequency Regulation Voltage Regulation Black Start
	Wholesale Market	Day Ahead Market Intraday Market
	Renewable Integration	Time Arbitrage Forecast Error Correction Ramp up Control
	Transmission System	Grid Stability
	Distribution System	Congestion Relief Peak Shaving Load Shifting
BTM	Commercial & Industrial	Increase PV Self -Consumption Tariff Optimization Peak Power Reduction Power Outages UPS Ramp Control Backup Power
	Aggregation	Virtual Power Plant Ancillary Services Demand Response
Microgrid	Off-Grid	Increase Renewable Share LCOE Optimization
	Grid Tied	Backup

Only a few countries have already exploited the functionalities of BESS, such as the UK and Germany for ancillary service applications and France with the renewable integration use case. Many countries are still marked as ”potential” since policy and market conditions are not positively aiding the diffusion of storage systems. It belongs to the scope of this work to better understand how profitable it is to use such systems to pursue FTM applications at the DS level. In the case study, a detailed zoom-in will be carried out for the Netherlands.

2.3. BESS Front-of-the-Meter Stakeholders: TSO and DSO

One of the largest groups of stakeholders concerns the grid operators. They are responsible for distributing electricity in several grids at different voltage levels, maintenance, and expansion of the grid. They are split into transmission system operators (TSOs) and regional or local distribution system operators (DSOs).

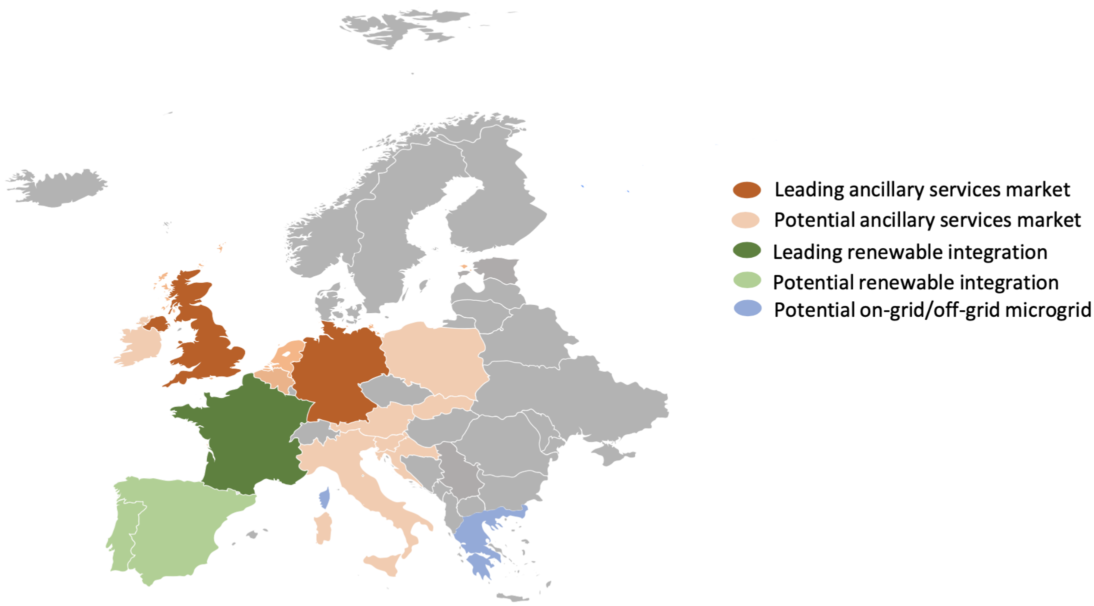


Figure 2.4: Map of battery energy storage system application in Europe - author elaboration from [15]

Transmission System Operator

The TSOs are responsible for the optimal and secure operation, maintenance, and, if necessary, expansion of their grids. They provide ancillary services such as frequency control, voltage regulation, and black start (i.e., restoration of supply systems). To accomplish TSO obligations is necessary to control the power to balance electricity generation and consumption in real-time. They often establish tenders to select new or old generation units to perform grid services, which turns out to be a suitable opportunity for battery system plant owners. Most of the time, TSOs are involved in Pilot projects which are typically initially a more miniature scale implementation of a larger project. They are used to work out issues and understand the revenues before entirely investing in the technology. For instance, in 2018, the Dutch TSO TenneT conducted a pilot project regarding the provision of Frequency Containment Reserves (FCR) through aggregators of different sources. Several clustered BESS have been tested for the provision of FCR in the Dutch market [20].

Distribution System Operator

The DSOs have the functional role of reinforcing and extend new or existing grid installations. Of particular interest is the relationship with DSOs since grid-tied ESS might be used to provide several services to local grid operators as seen from Table 2.1 .

As a result of the massive new installation of RES, more and more fluctuating load flows at various times of the year characterize the world grids. DSOs are nowadays facing new technical challenges due to the unpredictable nature of renewable energy generation assets (above all, solar and wind power) and Electric Vehicles (EVs) charging stations. In the context of improving the continuity of service of distribution grids, BESS can be deployed to ease the black start procedures. Furthermore, in case of fault that brings part of the DN to work disconnected from the primary transmission grid, storage systems permit islanding operation of the distribution feeder, allowing a safe operation also during unintentional islanding [21].

Currently, DSOs cannot hold a BESS that can influence the electricity market due to its liberalization achieved in 2004 [22]. However, by relieving the grid through the use of BESSs, DSOs would profit from different prospective i.e., reducing the power input peaks by achieving a delay or a waiver [4].

Another aid that BESS can bring to DSOs is flattening the generation and load profiles to decrease the maximum power at the grid point of connection (Peak shaving). This scheme can lead to waiving the network congestion and relieving the overloading of the conductors due to generation and load peak power [4]. In this application, energy storage might smooth also load profiles and support EVs charging stations. According to national grid codes, DSOs are required to guarantee the capability of the grid infrastructure. Thanks to BESSs, the network could accommodate both the irregular nominal power of the EV load and of a connected intermittent generator (i.e., solar plant). In this regard, increasing the profile matching between load and local generation, BESS operation can further reduce system losses.[5]. This application is among the research questions of this thesis, hence it will be further analyzed in a case study.

On top of these grid stability services, BESS at the distribution system level could be used for frequency control and energy arbitrage. These two applications will further be commented on in the following sections. To conclude, BESS will aid both TSOs and DSOs to achieve their common goal of providing an affordable and reliable electricity supply with the best renewable energy contribution.

2.4. Electricity Markets Outline

For a purpose beyond the scope of this thesis would be efficient to create an optimized model that can operate in the entire Continental Europe. However, nowadays, every country still has several local electricity markets with different rules, which are hard to combine. Shortly, Pan-European markets will be created, which will lead to a more uniformly distributed regulation and might give the correct input to expand further the model outlined in this thesis.

For a general overview of the European markets Figure 2.5 has been drawn. The electricity markets are divided by settlement period and market typology: wholesale, balancing, imbalancing, and capacity.

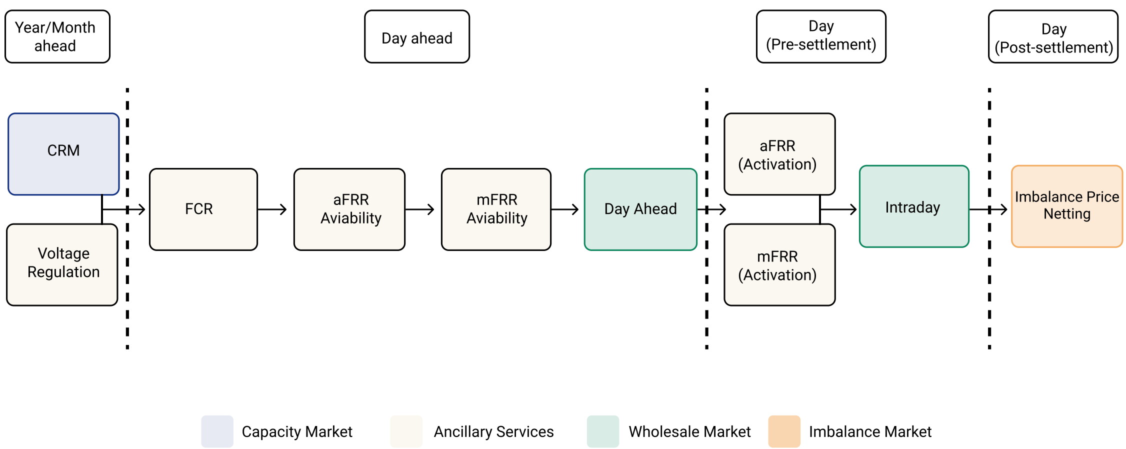


Figure 2.5: Electricity markets categorized for settlement period and service

In order to narrow the scope of the work, the focus will be placed on the Dutch electricity markets, which are seen as a part of a larger European electricity trading scheme. Germany will be used as a reference country in a specific case study. In the Netherlands, the electricity market can be approximately split up into four categories: forward markets, day-ahead market, intraday markets, and balancing markets [23]. The wholesale and balancing markets will be discussed below since several authors have categorized them as a potentially attractive market for BESS.

2.4.1. Wholesale Markets

The first three categories mentioned earlier (forward markets, day-ahead market, and intraday market) belong to the more extensive group of the wholesale market. This group covers the sales to large consumers and retail suppliers. Over the years, this market has become more and more international due to increased transmission capacity and harmonized market rules.

In trading, the base of the demand portfolio is covered for a yearly period. In forward markets, power is traded for years and months ahead via long-term contract, while most of the demand and supply are matched via day-ahead and intraday market. On the other hand, seasonal effects are dealt with with standardized trade blocks on a monthly or weekly basis. Long-term contracts are essential for market parties that do not want to be subject to short-term price volatility and seasonal effects. The portfolio manager adapts his net position to remain as close as possible to this new schedule. Hence, whether more power is required, its position is called short, otherwise long.

Day-ahead market

The day-ahead market (in this thesis abbreviated in DAM) is a response to this short-run trading. It takes place at 12h00 and market parties can trade electricity for the 24 hours of the following day. As a consequence, the trading takes place one day before the delivery (D-1). Here, sellers and buyers introduce offers and bids for an hourly time block and a specified amount of power (usually rated power). The settlement price is fixed at the intersection of offer and demand, and the remuneration is based on Marginal pricing (also called pay-as-clear). Such a method is a uniform pricing mechanism that offers the same price to all the transactions of a given product. The marginal clearing price (MCP) and the marginal clearing volume (MCV) are determined for every hour of the day.

Intraday market

After DAM gate closure, positions can still be adjusted on the intraday market. Such real-time markets are used to mitigate discrepancies between forecasted and actual demand, together with the risk of unplanned outages due to generation and transmission failures by adjusting energy and procuring additional capacity. [7]. However, the transactions are restricted by the TSO since they can impact the system's security. Moreover, electricity prices in the intraday are highly volatile and unpredictable since they are affected by various factors such as weather, contingencies in the power system, and all the physical constraints in the power system, especially if we are dealing with a considered amount of renewable assets [24] [25]. In the Netherlands, the intraday market is a continuous market. It enables continuous trading, and market parties can trade block hours, hourly products, and since December 14 2011, 15 min products can be traded up to 5 min before real-time [26]. In this mechanism, bids and offers are matched continuously according to incoming price proposals for the different time blocks. Consequently, there is no single clearing price in the market, but the price varies based on the bid matches. This price mechanism is called Pay-as-bid.

To conclude, the companies that participate in the market are called Balance Responsible Parties (BRPs). The TSO bears the final responsibility for the frequency stability and the balance between supply and demand. Therefore, the BRP applicant must sign a contract with the TSO setting out the rights and obligations of the two parties. A BRP would own the BESS simulated in this work with ”virtually” established agreements with the Dutch TSO TenneT BV to participate in the DAM.

2.4.2. Balancing Mechanism - Ancillary Services

The real-time operation of the electricity system delineates a third timescale. This phase typically starts at the so-called gate closure, the point in time until which orders are accepted in the market. After gate closure, the System Operator is in charge of managing the system centrally. In this phase, the generator can still make some profits if it can deliver services to the System Operator. These services are called ancillary services, and since the services are related to balancing, the notion of Balancing Service Provider (BSP) is also used. A BSP may be an electricity producer, a major consumer, an electricity supplier, or a trader. BESSs owners have all the right to be considered part of such a group.

Electricity demand and supply need to be matched in real-time and to achieve that, either a flexible demand or storage of power is necessary. When demand and supply do not match, the frequency deviates from the rated value of 50 Hz [27]. TSOs are entrusted with keeping the frequency of each synchronous area within defined bandwidths, defined by ENTSO-E, throughout constant monitoring and balancing the total power exchange [27]. Ensuring system balance in fast response is a key factor, and BESS technology due to their relatively fast response are particularly suitable for various balancing services [28] [15].

Frequency containment reserves

Primary Frequency Regulation, also called Frequency Containment Reserves (FCR) is activated automatically. If an imbalance is detected, the system operator can count on contributions to the primary reserve from all European transmission system operators. Procurement is obtained via the German platform Regelleistung and the remuneration is based on the availability via pay-as-clear (€/MW) mechanism [29]. The signals sent by TSO will activate the asset after a few seconds of imbalance in the system. The power output is adjusted according to a droop characteristic that follows the frequency deviation. Market participants can make a bid by offering a certain amount of power capacity. Whether it is accepted and activated, the contracted power must be up and running within 30 seconds. Additionally, limited energy resources, such as BESSs, are required to be able to keep the maximum power for frequency variations of 200 mHz for at least 15 minutes [30].

Frequency restoration reserve

In the Netherlands, the frequency restoration reserves (FRR) are further subdivided into automatic (aFRR) or secondary reserves and manual (mFRR) or tertiary reserves. Currently, the FRR pricing schemes are still based on a pay-as-bid approach and TSO TenneT has set up a BidLadder platform with an imbalance settlement period (ISP) every 15 min allowing market parties to bring all available flexibility to the market [29]. The remuneration is split into Activation (€/MWh) and Availability (€/MW). Since a pay-as-clear methodology facilitates competition, improves price formation, and attracts liquidity (provided the minimum required liquidity is available), the Commission Regulation establishing a guideline on electricity balancing encourages the implementation of a marginal pricing settlement scheme for activated FRR [27]. The following section will discuss the feasibility of the BESS to take part in frequency control services and energy arbitrage.

2.4.3. Consideration on BESSs Operating in Electricity Markets

In recent years, also ESSs connected at the DN have been allowed to provide frequency services. Though, the limitation given by their maximum and minimum State of Charge (SoC) might be considered an issue [12]. As far as Europe is concerned, literature studies have been conducted in a lower number of journals than in the US, where the business case for BESS is already known and exploited in many States.

Despite the standardized market product with easy access and its significant liquidity given by market coupling, business cases cannot only be built out of energy arbitrage. However, the day-ahead market (e.g., EPEX SPOT) presents little relevance for BESS. It is not possible to create a profitable business case with average day-ahead energy prices ranging from 30 €/MWh - 80 €/MWh in Europe [31] [32]. In a study conducted by [25], assuming a battery rated 1 MWh/1MW, the lifetime of 4000 cycles and the capital costs of 500 €/kWh, an average spot market price of 125 €/MWh would be necessary to drive a business case in case only energy arbitrage is considered. Therefore, European wholesale market prices might not be high enough to deem energy arbitrage as the only revenue stream because almost all types of energy generators have a lower cost than Li-ion batteries, whose technological advantages do not present any value within the use-case. On the other hand, the Dutch continuous intraday market system presents a significant opportunity for BESS, mainly to perform SoC management. Despite relatively low average price spread, being close to real-time market can result in high price peaks reflecting balancing needs due to the high short-term trading flexibility (up to 5 minutes GTC) and the European trading opportunities via XBID (Cross-Border Intraday) [29] [32].

According to [33], FCR, having high power to energy ratio, turns consequently interesting for BESS, especially for 1-hour systems. Such study has been conducted in Germany, which, as outlined in Figure 2.4 is a leading European country for BESS deployments. For now, FCR is the most valuable market for BESS in Europe. However, the introduction of a notorious amount of BESS is congesting the markets and lowering the prices up to 5 – 10 €/MW/h, as seen in Germany [9].

Nevertheless, according to [34], the batteries, during their service, after years of operations, will experience energy losses due to degradation of their cells and the electronic components interface to the electricity grid. Moreover, due to their limited capacity, they will not be able to provide FCR alone for infinite periods. Its energy level has to be restored either directly (i.e., restoration from a power plant) or through energy arbitrage with energy management purposes.

Besides, [35] states that the implementation of storage units in the voltage control scheme (Voltage regulation service) is technically effective and easy to implement, given BESS reactive power capability [35]. However, since the remuneration (€/MVarh) for the activation is fixed in the form of Bilateral Agreements and achieved via tenders [36], its modeling will not be taken into account in this work.

In order to examine current challenges, a study on a BESS at DS level is conducted in this thesis. The electricity flowing through the battery can be sold at the spot market or ensured to supply upward and downward regulations of the FCR market, with part energy or the power surplus being used to offer additional service to the DSO.

2.4.4. Current Policy Challenges in the Netherlands

From a policy perspective, as claimed by [37], currently, in the Netherlands regulatory barriers and market barriers are slowing the expansion of ESS to participate in the electricity markets.

Among the regulatory barriers, the absence or inadequacy of legal classification is crucial. Currently, storage facilities are classified as generators and consumers, and since no legal definition is defined for being both in one, they are double taxed. This makes the electricity very expensive and reduces the profitability of a BESS. In addition, energy storage entities are not registered as RES. Therefore, they fall out of scope for any RES incentive receiving only a few financial incentives for time-shifting applications. Moreover, as already mentioned, grid operators are not entitled to owning storage facilities due to the open electricity market system. Up to date, no regulatory framework exists that states BESS could benefit from providing services to the grid.

2.5. Optimization for BESS Design

An in-depth review of general energy systems optimization methodologies is outside the scope of this section. These paragraphs aim to provide some context to the model upon which this thesis is based, rather than give a detailed explanation of all the proposed optimization techniques applicable to energy market modeling.

Optimizing energy systems design is a complex problem that requires considering many factors, technologies, and scenarios. Different methodologies have been proposed in the literature depending on the size of the system, the technologies, and the formulation of the objective functions. Among these, the vast majority rely heavily on computational techniques rather than on analytical solutions.

2.5.1. BESS Common Electricity Market Challenges

Optimization techniques can be distinguished based on their scope, approach, degree of approximation, dependency on explicit assumptions, and many other features. The way energy systems are represented in mathematical terms varies widely, depending on both the focus and the starting points of the different methodologies [38].

As claimed by [39], the operation of an energy storage system may be formulated as an optimization problem where the cost function is defined either from a financial point of view or from the electricity grid benefit. A hybrid version as a combination of the two is also possible. The constraints are imposed by characteristics of the energy storage system technology and the system's settlement. In order to operate in different market performing multiple ancillary services application, several authors [6] [33] [25] [7] divided their models in different set with different time resolution. Generally, energy arbitrage and ancillary services are supplied for different time scales. The first one is supplied based on hourly prices while frequency regulation is conducted for 15 min. Hourly optimization does not capture decisions on smaller time scales. On the other hand, if a smaller time step is selected, it is hard to manage the size of the optimization problems and conduct a full-year optimization with many decision variables and constraints. For this reason, it is challenging to optimize the operation of BEES for multiple services simultaneously. Different approaches are proposed in the literature. The paper [6] determines each service's optimal level by pre-allocating the BESS's energy and power capacities. In the study, the optimal power capacity sharing could be 40% of MW capacity for frequency regulation, 60% of the MW capacity for energy arbitrage. This allocation can be conducted by studying the data and see which market is more profitable than others. In addition, the author [6] agrees with [33] about BESS being very effective in frequency regulation due to the composition of the system and the cells used.

In line with [40], if the design of energy systems is the target, the scheduling problem should be taken into account, which is related to the estimated operative revenues of the system. For a given system design, stochastic programming, dynamic programming, or optimal control are often utilized to analyze the performance of a system dependent on the scheduling. However, a two-stage approach will be adopted to simplify the thesis model, reduce the computational requirements, and contain the complexity of the assumptions and inputs. This implies that the difference between the scheduling problem solution and the optimal operational strategy does not significantly affect the optimal system design. Deterministic optimization and perfect foresight will be adopted as a first stage outcome; secondly, the specific result will be shaped.

The duration of the simulation is another problem tackled in the literature. In [7] the revenue potential of energy storage technologies from historical price signals have been calculated for a year. However, it is relevant to stress the attention on the fact that with such a short simulation is tough to create a concrete, valuable strategy. The authors [7] mention a practice called virtual bidding. Here the simultaneous sale and purchase of energy occur, i.e., purchasing energy on one market (e.g., day-ahead) and reselling it on another (e.g., intraday) simultaneously. In this way, the revenue stream further increases. However, such application is not regulated yet in Europe; therefore, it is not applicable in our case. Furthermore, fast flexibility in energy systems is a determinant factor for higher revenue chasing. Besides all, costs of fast charging and low SOC operation are not included in any model analysis.

Concluding, every paper's purpose here addresses the main concerns of BESS owners for maintaining the optimal operation of their units and gaining maximum profits. Only a few papers consider supplying energy arbitrage and ancillary services from the same BESS to maximize profit. Usually, just one of the two applications is turned to account [38]. Overall many authors conclude that only day-ahead markets and or energy products underestimate revenues and the capabilities of the batteries. The combination with ancillary services capitalize higher revenues [6] [7] [41] [42]. Other authors aggregate BESS with other BSP or RES [8]. The power capacity, the energy capacity, and the reactive power capacity should be shared simultaneously to supply ancillary services and conduct energy arbitrage, which costs several activations of the BESS. A trade-off between cyclability and max profit would be necessary for a more realistic draw of the business case [6].

2.5.2. Linear Programming Models

In the world of optimization for energy systems, approaches based on linear programming (LP) and its extensions have been widely used and discussed. Besides techniques derived from linear programming, many other approaches have been proposed and articulated. On the other hand, integrated or multi-market energy models often rely on more general mathematical formulations as deterministic optimization [7].

Linear Programs (LPs) have been applied to the optimization of energy systems for more than 30 years [40]. They are mathematical problems with linear constraints, real variables, and convex feasibility regions and are among the most powerful and widely adopted optimization frameworks.

The main advantage of LPs is that linearity ensures the convexity of the problem. As a consequence, LP problems can, in most situations, be solved exceptionally efficiently, and their solutions have a set of highly desirable features from a mathematical perspective. On the other end, the two main limitations of LP models in terms of applicability consist of the impossibility of representing non-linear functions and taking into account discrete and binary variables. For instance, the optimization in battery energy systems requires binary variables to describe the charging and discharging of the asset. Furthermore, cost functions and efficiency curves can be highly non-linear, making LP models inaccurate. An additional issue with linear models is their sensitivity to input data. Indeed, their linearity itself causes the optimal point to be always located in an extreme position within the feasibility region, more precisely on its frontier [40]. As an example of LP applied to BESS optimization problems in [39], an LP model is used to optimize the operation of a BESS for energy arbitrage. The cost savings from arbitrage can be estimated from market data using a Linear Program (LP) optimization, as seen in [38].

Many authors have used linear programs to model systems of different sizes in energy systems design, but recently Mixed Linear Programming (MILP) models have gained more attention. Such formulation will be exploited in the frequency market decision making to differentiate upward from downward bid as in [6] MILP models represent a partial solution to some of the limitations of LPs mentioned in the previous sections: binary (and integer) variables can be included, and non-linear functions can be approximated through piece-wise linear functions built through binary variables [40]. This increased applicability does not come without consequences: MILP problems are harder to solve, and the computational time required for their solution can be exponential relative to the number of integer variables. In power systems, mixed integer programming is often applied to solve the day-ahead unit commitment (UC) problem for generators and near real-time economic dispatch. Specifically, several authors [17] [38] have modeled the energy arbitrage of BESS with balancing services application. Constraining specif variables as integers returns helpful for problems where there are on/off states of specific assets i.e., generators in UC problems or BESS activated in upward/downward frequency regulation.

2.6. Evaluation of BESS Lifetime

The capacity loss, or capacity fade, of the system is affected by many different factors. Electrochemical and mechanical degradation and power electronic wear play a relevant role in evaluating the performance loss upon use. Research has shown that both the power cycling and the idling condition contribute to the aging of batteries [28].

In [43] is examined the bond between the capacity fading of a battery and the C-rate since high C-rates lead to faster fading per cycle. The C-rate determines a ratio between a battery system's power and energy output, i.e., a battery with a C-rate of 1 can fully discharge the stored energy within one hour. Moreover, some technologies, as the Li-ion battery, suffer from severe capacity fading if they operate at the upper or lower limits of their installed volumes [44]. The temperature also strongly influences the Li-ion battery capacity fading [16]. Overall, battery cells are subject to several aging mechanisms. Independent of the chemistry, the aging processes are generally complicated and dependent on the operating conditions. For Li-ion batteries, the main ones are calendar aging and cycling aging. They are evaluated according to the empirical equations (2.1) and (2.2) respectively [16]:

$$C_{cal}\,(25°C) = 1.72 \cdot 10^{-1} \cdot e^{7.38 \cdot 10^{-3} \cdot SoC^{*}} \cdot t^{\frac{4}{5}} \tag{2.1}$$

$$C_{cyc}\,(25°C) = 2.11 \cdot 10^{-1} \cdot e^{-1.94 \cdot 10^{-2} \cdot SoC_{avg}} \cdot cd^{7.61 \cdot 10^{-1}} \cdot nc^{\frac{1}{2}} \tag{2.2}$$

The above equations the average SoC of a cycle SoC_{avg}, the number of cycles nc of a certain cycle depth $cd,$ and the idling time t of the battery at a certain SoC level SoC^{*}. The formulas are valid at Standard Ambient Temperature (SAT) that ensure the best performance.

According to [16], Li-ion batteries are aging both during use and storage. The first one is affecting the calendar lifetime of the battery, while the second one is affecting the cycling lifetime of the battery. Additionally, Lithium-ion based batteries have a limited lifetime, strongly influenced by the cycling pattern and which generally spans from 3 thousand to 10 thousand cycles, depending on the lithium technology and the cycling conditions, as seen in Figure 2.2. Aging mechanisms lead to a lower battery's energy capacity, power capability, and round trip efficiency. In respect of Li-ion technology, in literature, a capacity fading of 20% is commonly considered as a reference value for the End of Life (EoL) of grid-connected BESS [45].

Besides the cell aging effect, the power electronic wear constitutes an essential factor for evaluating BESS's lifetime. As displayed in Figure 2.3, power electronics enable to interface the battery storage with the AC grid. An exhaustive evaluation is given in [28] where the degradation of IGBTs and electrolytic capacitors have been studied through a 150kW/150kWh BESS performing FCR. These fading effects are mainly driven by the thermal stress to which they are subjected. As a result of the study, the more subjected to faster degradation is the electrochemical storage, with a lifetime range of 10-11 years, depending on the case scenario. The other two components analyzed, however, do not show significant wear due to continuous FCR operation. The reason is bonded to the type of ancillary service that makes use of very little power utilization. However, no conclusion can be withdrawn with BESS performing other services, such as energy arbitrage, peak shaving, and other combined services for the DSO, which would require BESSs with a higher energy capacity.

3

Design Model Formulation

In this chapter, the model of a profit-maximizing BESS operating in different markets is illustrated. The proposed model considers that the system can participate in energy arbitrage and primary frequency regulation as ancillary service and offer remunerated services to the DSO.

3.1. The Methodology and the Model Components

The methodology of this research is structured as follows. First, the mathematical optimization problem of energy dispatch has been tailored to BESSs. Secondly, the linear problem has been reported in a Python-based simulation environment, using the Pyomo optimization library. Since Pyomo is a modeling library, it requires a solver to solve the model, which can be called directly from the simulation environment. Any solver compatible with Pyomo is applicable for executing the optimization model, however, only a few of these are available open-source, such as glpk or cbc. The solver glpk is only suitable to execute LP problems, and thus, the available options are narrow and not suitable for the project. Nonetheless, commercial solvers are much more powerful and can provide a better performance, which brings additional value to the tool, particularly in the case of a complex model that would otherwise take a long time to execute. In order to exploit the wide range of compatibility of Pyomo and expand the selection options, Gurobi resolution strategy was selected, which becomes available for academic use without the need to purchase the commercial license.

Moreover, in this section, the factors involved in the optimized bidding strategy are displayed. The model optimizes the power flows between the BESS, the Wholesale Market or Day-ahead market (DAM), the Primary frequency regulation (PFR) or Frequency curtailment reserve (FCR), and the DSO operation module to return the most significant revenues. Along with the chapter, the abbreviations DAM and FCR will be used to indicate the respective market.

Figure 3.1 depicts every module, including their corresponding interconnection data exchange. As mentioned, the complete model is implemented inside a Python-based simulation environment. The Python-based framework offers state-of-the-art single objective optimization algorithms and is designed to be extendable and applicable to various battery technology and electricity markets due to its modularity in code development. Furthermore, the algorithms are highly customizable and can easily be tailored to user needs. First, the code starts with providing an upper limit of the achievable profits of BESS for market participation since it is based on perfect foresight regarding electricity prices. Secondly, block timesteps are introduced to evaluate the DSO operation combined with an existing fast charging-solar integrated system. In this way, part of the running hours is reserved for testing the possible benefits that both DSO and the owner of such system might encounter while combining their activities with the BESS.

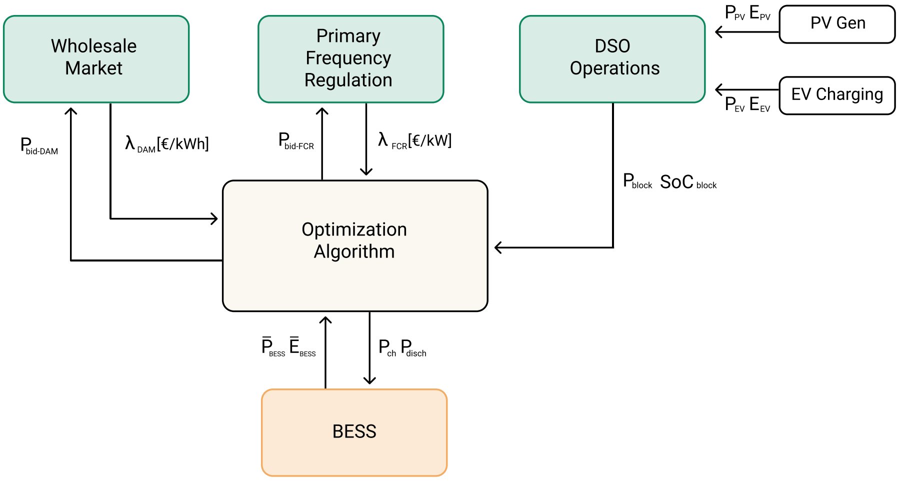


Figure 3.1: The model set up shows the virtual exchange of information among the different modules composing the optimization: Wholesale Market (DAM), Primary Frequency regulation (FCR), DSO operations and the BESS

Figure 3.2 displays the flowchart, which explains the logic behind the optimization algorithm. From its logic, it can be inferred that any battery operation is only possible when the DSO is not reserving the total capacity for its business. In that case, the revenue is calculated speculating on the service offered. On the other hand, to obtain the highest remuneration, the BESS must be in the legal condition to be committed for FCR. The wholesale module is also executed anytime to enable the asset to perform such a service. The terms wholesale module and primary frequency regulation module refer to the DAM and FCR market participation.

3.2. The Mathematical Optimization for Energy Arbitrage & Frequency Regulation

The developed model proposes a general optimization framework to capture diverse revenue streams provided by wholesale electricity markets and ancillary services. Precisely, the framework models DAM and FCR.

The model is provided with perfect foresight. Therefore, actual market prices are assumed to be known upfront, leading to the maximum reachable fictional revenues. The market prices remain unknown in advance in real life since they are based on a bidding mechanism. In particular, for DAM, the Gate Closure Time (GCT) is at 12.00h every day, while for FCR, the GCT is every morning at 8:00h and creates a bid for the six blocks of four hours in the following day. Moreover, the spot and FCR markets bids are assumed to be entirely accepted (i.e., bidding at 0 €/MWh). Consequently, the resulting revenues will be an overestimation of the actual revenues of a real deployed BESS.

Wholesale electricity markets introduced varying electricity prices during the day based on the intersection of aggregated supply-demand curves for each hour block. For energy arbitrage, the asset will participate in the DAM bidding the energy capacity and maintaining a constant output power over each block period. The FCR market is modeled optimizing the participation according to the FCR market price [46]. It is assumed that the battery assets are activated each time since it is the cheapest feasible bid that guarantees the necessary regulating power in the defined control area. However, the device cannot track the frequency signal and detect a deviation from the nominal frequency. Moreover,

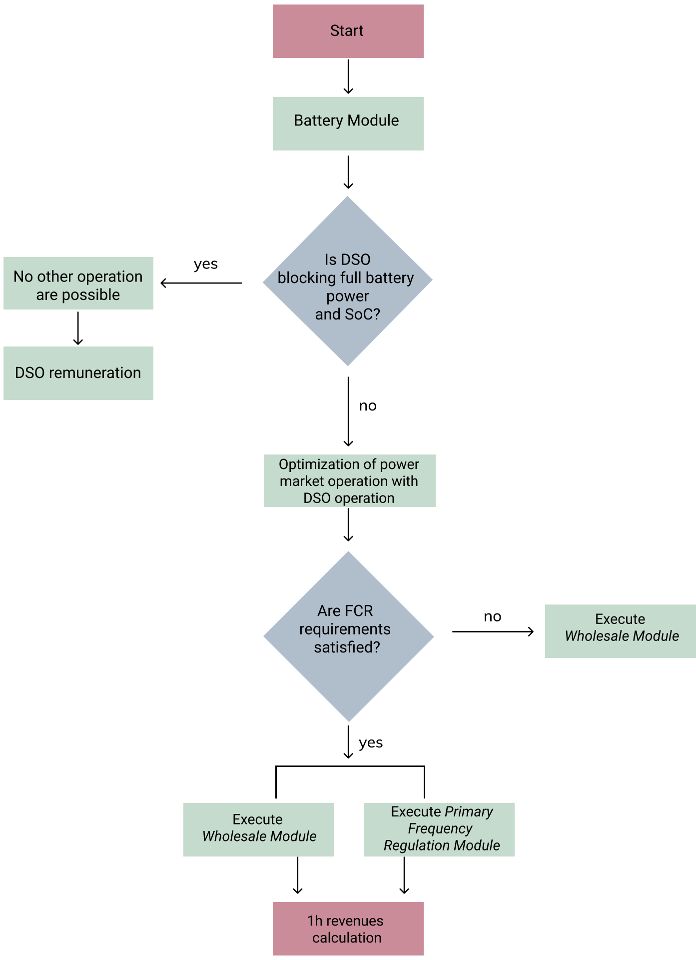


Figure 3.2: Flow chart of the algorithm. Every optimization timestep, the algorithm follows the logic displayed to maximize the revenues of the BESS. The DSO operation block is the first constraint. If full capacity is given to DSO, no other operations are possible. The execution of FCR is subjected to regulatory requirements. The execution of the wholesale module could help to fulfill them, maximizing the range of operations

it cannot adjust its active power output according to the droop characteristic that follows the frequency change.

The components of the mathematical optimization problem are illustrated in the following sections. First, the constraint of the problem, together with the battery boundary condition, is exposed. Lastly, the maximizing objective function is presented.

Constraints

The constraints of the system are divided into battery operative boundaries, market requirements, and DSO operations.

1) Battery system

In general, batteries have rapid response times. They can quickly switch between charging, discharging, and idling, making them a promising technology for ancillary services applications. The typology of battery and the size have been selected compatibly with the TSO's (TenneT) obligations [29]. However, for the sake of the research, the system refers neither to a particular type of technology nor the location of market operation. Such parameters are used as input in the model.

The first set of constraints includes the modeling of the battery functioning (3.1) - (3.4). The power battery boundaries are shown in (3.1) (3.2). While the energy limits are defined in (3.3) (3.4).

$$0 \leq P_{disch}[t] \leq P^{*}_{disch} \; \forall t \tag{3.1}$$

$$0 \leq P_{ch}[t] \leq P^{*}_{ch} \; \forall t \tag{3.2}$$

$$P_{disch}[t] \leq \delta_{batt}[t] \cdot P^{*}_{disch} \tag{3.3}$$

$$P_{ch}[t] \leq (1 - \delta_{batt}[t]) \cdot P^{*}_{ch} \tag{3.4}$$

$$SoC[t+1] = SoC[t] + \left(P_{ch}[t] \cdot \eta_{ch} - \frac{P_{disch}[t]}{\eta_{disch}} \right) \cdot \frac{t}{E^{*}} \tag{3.5}$$

$$0 \leq SoC[t] \leq 1 \; \forall t \tag{3.6}$$

$$SoC[t_0] = SoC[t_n] = 0.5 \tag{3.7}$$

The updated SoC of the battery in each time interval is calculated in (3.5) and applies the state of battery operation (charging or discharging) according to the limits on the SoC. Modeling the SoC management of an electrochemical battery is out of the scope of this thesis. Some models can vary widely in terms of complexity since they can be designed as a function of voltage and current profile, temperature, and battery age [33] [41]. Furthermore, the conversion efficiency of Li-ion batteries can be intensely dependent on the SoC and charge/discharge power level. A more accurate model would employ different parameters for these systems, introducing a non-linearity that makes the optimization problem harder to solve. Additionally, no decay per hour is taken into account.

The limits for battery SoC are defined in (3.6). Since the model is not linked with one type of technology, the DoD and DoC are set to 0 and 1, respectively. Equations (3.7) assumes that the battery has an initialized state of charge. For physical limits, the BESS cannot be charged and discharged simultaneously:

$$P_{ch}[t] \cdot P_{disch}[t] = 0 \tag{3.8}$$

The binary variable δ_{batt} is introduced to help to linearize (3.8). Consequently, (3.3) and (3.4) are obtained. Currently, the limit on the battery cyclability is not strictly imposed since it also depends on the type of system applied, as displayed in Figure 2.1.

2) Market requirements

The DAM and FCR markets have different block duration. Therefore the time discretization is based on two levels. Level 1 comprises one-hour time intervals in the DAM $t \in [t_0 ... t_n]$. While level 2 corresponds to the four-hours frequency market $z \in [z_0 ... z_n]$. An indexed mapping study has been conducted deeply in [7], from which is derived the timestep coupling of the model. A ramping rate is the maximum amount of electricity that a system can deliver in a one-time step. The market with the lowest resolution (DAM) is used as the default timestep for that purpose. According to the time increment employed by the market (i.e., 1 hour), the device will charge/discharge at the commanded power level over the market time increment. For example, in a day-ahead energy market with a 1-hour time increment, the BESS would maintain a constant charge/discharge level for the 1-hour timestep. Future work will be developed a function that looks for the lowest resolution.

The model equation for FCR are gathered in (3.9) - (3.12). According to [47], the minimum bid of FCR capacity is 1MW, which is constrained as (3.9) and (3.10) [30]. However, in this study, a BESS rated 500kW/500kWh has been considered, assuming that the BESS is aggregated with other balancing service providers (BSPs) to reach the minimum required power for FCR by clustering together up to 1 MW. Furthermore, the TSO allows divisible and indivisible bids. Indivisible bids can have a maximum bid size of 25 MW, which is far above the size of our BESS [30].

Another binary variable, γ_{fcr}, is introduced to indicate whether the TSO requires FCR regulation. It is assumed that the electricity flowing into the battery does not influence the SoC during the service and once completed. Furthermore, as stated in [48] the sum of the maximum power for SoC management and the FCR is always equal to the maximum system power. In order to take into account the SoC management power that should be reserved for FCR, an 80% factor is used to limit the $P_{fcr_{bid}}$. This parameter taken from [28] is obtained as the optimal point that leads to the lowest components degradation with the highest NPV based on a time horizon of 25 years. Many other effects are not considered, i.e., the re-establishment of the SoC at the half, with the maximum energy available, in case of a strong frequency perturbation. On the other hand, other relevant constraints are simulated and discussed in the following paragraphs.

As for limited sources, supply must occur as soon as the deviation happens and for at least 15 minutes. This can be translated that the SoC while performing FCR cannot be either lower than 25% or above 75%. The reference SoC value is indicated in the equations as Γ. This constraint is expressed via (3.11) and (3.12). In many European countries, the FCR bid is symmetric. The symmetrical bidding for upward and downward regulation capacities are constrained as (3.13).

$$\beta \cdot \gamma_{fcr}[z] \cdot \leq P_{fcr_{bid-up}}[z] \leq \gamma_{fcr}[z] \cdot P^*_{disch} \tag{3.9}$$

$$\beta \cdot \gamma_{fcr}[z] \cdot \leq P_{fcr_{bid-down}}[z] \leq \gamma[z] \cdot P^*_{ch} \tag{3.10}$$

$$-SoC[z] \cdot E^* \leq -P_{fcr_{bid-up}}[z] \cdot \Gamma \tag{3.11}$$

$$(SoC[z] - 1) \cdot E^* \leq -P_{fcr_{bid-down}}[z] \cdot \Gamma \tag{3.12}$$

$$P_{fcr_{bid-up}}[z] = P_{fcr_{bid-down}}[z] \tag{3.13}$$

As mentioned, modeling the battery activation response due to the frequency deviation is out of the scope of this work. The possibility to split the power and bid simultaneously in both markets is shown in equations (3.14) and (3.15). Additionally, these equations determine that buying and selling within one timestep is allowed in the model. For example, electricity bought on the DAM can be directly committed to the FCR market, yet it cannot be sold to DAM again. Nevertheless, whether it is established to commit only frequency regulation, equations (3.16) and (3.17) are enforced and bidding in both markets is avoided.

$$P_{disch}[t] + P_{fcr_{bid-down}}[z] \leq P^*_{disch} \tag{3.14}$$

$$P_{ch}[t] + P_{fcr_{bid-up}}[z] \leq \cdot P^*_{ch} \tag{3.15}$$

$$P_{disch}[t] \leq \left(1 - \gamma_{fcr}[z]\right) \cdot P^*_{disch} \tag{3.16}$$

$$P_{ch}[t] \leq \left(1 - \gamma_{fcr}[z]\right) \cdot P^*_{ch} \tag{3.17}$$

3) DSO Operations

In order to integrate the DSO interaction with the BESS in the optimization problem, the following equations are introduced:

$$P_{out}[t] + P_{FCR}[z] + P_{block}[t] = P^{*}_{rated} \tag{3.18}$$

$$P_{out}[t] \cdot \eta_{disch} = P_{DAM-sell}[t] + P_{FCR}[z] \tag{3.19}$$

$$P_{in}[t] = (P_{DAM-buy}[t] + P_{FCR}[z]) \cdot \eta_{ch} \tag{3.20}$$

First of all, equation (3.18) expresses the power balance of the system for every time step. The power flowing in and out of the battery system needs to be equal to the energy sold or bought on the DAM and the power used to procure FCR. Furthermore, some of the available power and SoC have been reserved for auxiliary operations. Therefore blocks parameters (P_{block}, SoC_{block}) are introduced to simulate the DSO activities. In particular, (3.5) is updated as follows:

$$SoC[t+1] = SoC[t] + \left(P_{ch}[t] \cdot \eta_{ch} - \frac{P_{disch}[t]}{\eta_{disch}}\right) \cdot \frac{t}{E^{*}} + SoC_{block} \tag{3.21}$$

in which the block values SoC_{block} are negative if the battery has to provide energy and positive when energy is stored into the system. An extensive description of how they have been calculated is provided in subsection 4.4.2. Their effect will be shown in the last section of this chapter.

Moreover, the out and inflow of electricity to the BESS is subject to efficiency loss. These statements lead to the constraints (3.19) and (3.20). Among TSO's guidelines, the BESS controls outputs should not use the dead-band of the P-f droop control curve for FCR provision for regulating the SoC, yet a fraction of the power should be maintained to perform SoC management [48]. This conversion efficiency does not take into account the SoC management power that should be reserved.

Objective function

The profit-maximizing objective function of the mathematical model is described in (3.22), (3.23) and (3.24).

$$\underset{P_{disch}, P_{ch}, P_{fcr_{bid-up}}}{\mathbf{Maximize}_{(\mathbf{t},\mathbf{z})}} \; DAM[t] + FCR[z] \tag{3.22}$$

$$DAM[t] = \sum_{t}^{t_n} (\lambda - C_{ramp}) \cdot P_{disch}[t] \cdot t - \sum_{t}^{t_n} (\lambda + C_{ramp}) \cdot P_{ch}[t] \cdot t \tag{3.23}$$

$$FCR[z] = \sum_{z}^{z_n} P_{fcr_{bid-up}}[z] \cdot (\lambda_{fcr} - C_{fcr-ramp}) \cdot z \tag{3.24}$$

The terms the equations above represent the revenues from the volumes of electricity sold on the DAM and the FCR markets multiplied by the respective market price (λ and λ_{fcr}) of that time slot.

A ramp cost is instituted C_{ramp} to guide the decision-making process and reduce the battery cycles. The value of this parameter represents the marginal cost of the system (the O&M cost normalized based on the average of 1 cycle per day) [32]. Such opportunity cost means that at least 8-8.5 €/MWh price spread are needed for the DAM to be effective. The same strategy has been adopted for the maximization of FCR market participation. Indeed, $C_{fcr-ramp}$ represents the ratio of the sum of the cost of the battery system and the Balance of Plants on the max operative hours in a year. The figure oscillates around 13-14 €/MW. By mean of those two "ramp costs", the battery number of cycles is constrained and lower than 600 per year.

Additional Constraints

The exhaustive cycling of the battery can result in reaching the end of life sooner than expected. Thus, it is important to keep track on the number of cycles by calculating it, and possibly limit the cycling. According to literature [16] for Li-ion technology a cycle limitation of a one year equivalent cycle is a fair consideration. It is also possible, to keep a buffer in case it is beneficial to cycle it more, so a slack variable is introduced, in order to provide a soft limit. As the slack variable can be positive or negative, not cycling the battery is also valued. For the current model such variable is left tending to infinity in order to do not limit the possible operation as seen in the following equation:

$$\begin{cases} \sum_{z=z_0}^{z_n} \gamma_{fcr}[z] + \sum_{t=t_0}^{t_n} P_{disch}[t] \cdot \frac{t}{\eta_{disch}} \leq n_{max-cycles} + s_{cycles} \\ s_{cycles} \mapsto \infty \end{cases} \tag{3.25}$$

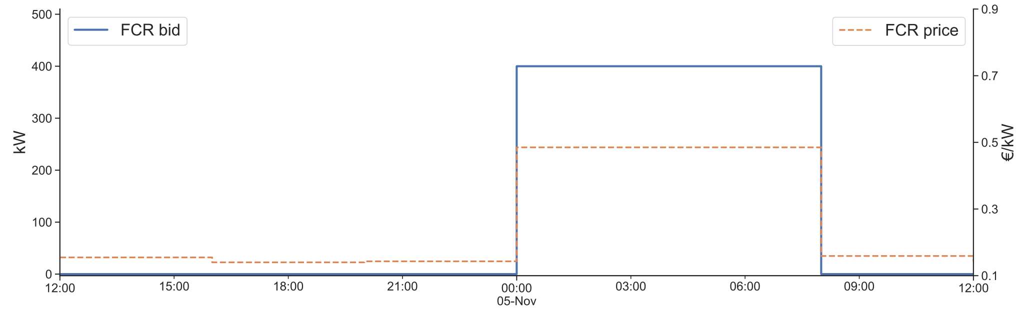
To conclude, the mathematical problem is formulated only for the scope of dispatching the available asset. Further analysis, calculations, comparison of different scenarios are realized outside of the optimization itself.

3.3. Model Performance

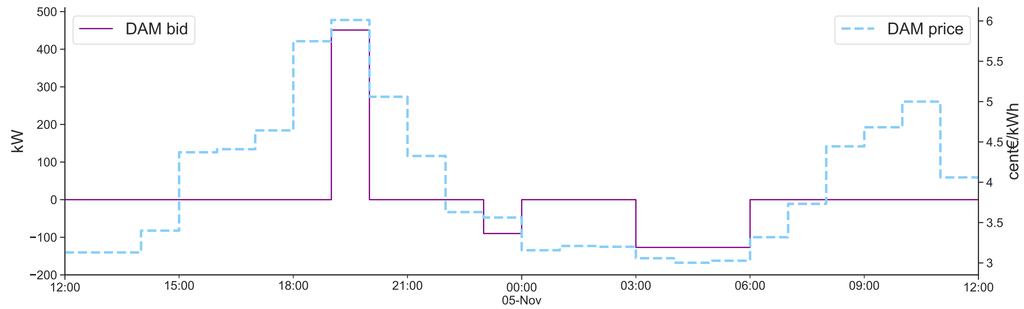
In this final section, the performance of the model is evaluated considering 24 hours astride of the 5^{th} of November. The BESS used as reference is rated 500kW/500kWh with a round trip efficiency of 90%, which can be fully charged in one hour or one timestep.

Figure 3.3 illustrates how the power is dispatched by the system and how the price-driven optimization performs for FCR market (Figure 3.3a) and for DAM (Figure 3.3b). The battery will be commissioned to perform FCR for 8 hours only when the price is much higher than the other hours of the day. On the other hand, it performs energy arbitrage during the most favorable price slots of the day, i.e., discharging when the price is the highest and charging when it is the lowest. However, due to FCR and DSO-operation model constraints, this type of schedule is not always possible. The specific case can be noted in Figure 3.3b when right before midnight, although the price was not optimal (i.e., it was even lower a couple of hours later), the BESS buys energy from the market. This effect is attributable to the ”perfect foresight” method used in the model. A more price-beneficial operation (FCR) was supposed to occur in an hour, yet the SoC was nearly zero, and it would have excluded the possibility to perform FCR for the following settlement period. Thus, the BESS charges enough to satisfy the constraints (3.11) and (3.12) by leveling the SoC at 25%.

Additionally, from the timeslot, 3 AM-6 AM, the double bidding function is showed, which means that no constraint limiting the participation in both markets is active. Mathematically speaking, the constrain is defined as inactive (non-biding). Further results on the effect of this constraint are examined in chapter 5. As could be noted in the same slots, the optimization algorithm controls the discharge by placing consecutive bids to increase the level of charge of the battery gradually. The optimization is aware that the price will maintain low for some timestep, hence prefers to fill the cells progressively improving the lifetime, rather than using a full cycle bid. Furthermore, the total bid capacity for FCR is only 80% of the nameplate capacity due to efficiency losses and the SoC management constraint.



(a) Primary frequency regulation market BESS behavior

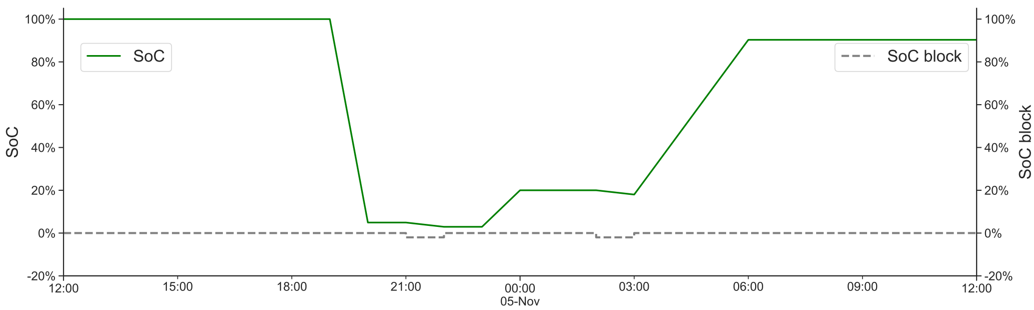


(b) Day-ahead market BESS behavior

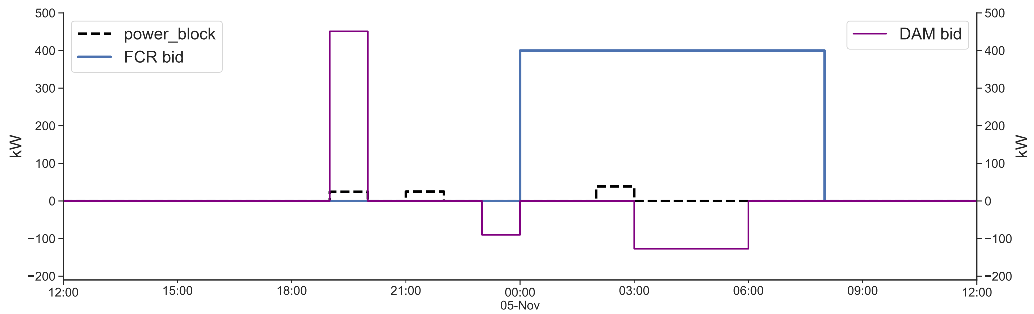
Figure 3.3: Profit maximizing BESS participation in Day-ahead market and Primary frequency regulation market for a sample 24h time-shift

Figure 3.4a the SoC of the battery is depicted. Comparing the SoC trend with the overall power output of the system, it may be noted how only the DAM bid and SoC_{block} influence the SoC variation. As a direct consequence of being an energy market, the volume traded in the DAM drives the charging level of the battery. On the other hand, the charging station demanding extra battery capacity, i.e., negative SoC_{block} values, leads the SoC to drop accordingly. The primary frequency regulation affects as well the SoC generating a continuous oscillation. Nevertheless, such behavior has not been modeled. It is assumed that the SoC at the beginning and at the end of the service does not change.

In Figure 3.4 zooming carefully at 18.00h, the plot displays why the battery did not dispatch at total capacity in DAM, answering why the SoC was nearly zero before performing FCR. This limitation can be conducted to the impact of the allocated power requested by the DSO (P_{block}) for its operation. The power that the DSO can block has hourly timestep, however, the period might be much shorter, hence no SoC_{block} is noted.



(a) BESS SoC trend



(b) Combination of the three BESS power operations considered

Figure 3.4: Comparison between BESS operations and its state of charge for a sample 24h time-shift

4

Case Study Data Analysis

The optimization algorithm is validated with 2 case studies. The first concerns the trade volumes that maximize the value of trades made in the DAM and FCR. In order to understand the business case, the comprehension of the input prices involved is needed.

The goal of the first case study is to assess the revenues coming only from market application. While to evaluate the business case for BESS in DNs, a second case study is formulated. The second case study applies to a general distribution system application where the DSO must integrate a Photovoltaic (PV) - Fast Charging (FC) station owner and a BESS owner in a single point of connection. The benefit for each of the three players involved (DSO, PV-FC station owner, and BESS owner) is illustrated via such case study.

In this chapter, an introduction and an analysis of the data are performed. At first, a price framework has been developed in order to evaluate the input prices. Secondly, the possible future revenue streams are investigated by a price-driven forecasting method applied to the DAM dataset. Finally, the PV-FC station environment for the second case study is introduced.

4.1. Price Generation Framework

Significant inputs to the optimization model are the day-ahead market (DAM) price (λ) and the primary frequency market (FCR) prices (λ_{fcr}). For this study, no point forecasts were available for these price processes. Hence, the goal of this section is to construct point forecasts for each. Firstly, an analysis of the historical DAM prices is performed. Secondly, the methodology is discussed based on the literature on forecasting electricity prices.

4.1.1. Data Collection and Assumptions

The model's market data inputs can be categorized into two categories: historical data of DAM and FCR prices for the Netherlands and Germany and future market price scenarios obtained with forecasting algorithms.

Despite the ample availability of public energy data on the web, obtaining consistent and reliable energy price data for a controlled geographic region was a significant challenge. The transparency platform of the European Network of Transmission System Operators was used to obtain spot market data from 2016 to 2020, as well as FCR action prices from June 2019 up to April 2021 included. The DAM prices for 2019-2020 were benchmarked with Nord-Pool [49] for the Netherlands and Germany, while the Regelleistung platform was used to merge the FCR prices of the respective countries [46]. Inconsistencies were not found, however, both countries joined such platforms only in 2019, therefore no previous data were displayed. Furthermore, the data were also compared with the statistics published by TenneT in its yearly reports [50] [51] [52]. Besides, in the simulations, the data from the daily delivery periods have been up-sampled. In fact, until July 2020, the FCR market was split into daily delivery periods. Only starting from July 2020 on-wards, price data for the Four-hour blocks. Starting from the Regeilleistung value, which has been treated as cap value for the two auctions during the night, a Gaussian distribution was applied to obtain six values (blocks), one for each delivery period. The Gaussian distribution was chosen as it reasonably approximated the price behavior over the day [2]. In this way, the resulting value has been scaled to meet the simulation resolution of a 4hours timestep.

Before starting with the analysis of the specific case study, some assumptions are made in the follows:

- The predicted values for the power generation, the DAM prices, the FCR market prices are assumed to be known beforehand based on historical data.
- The DAM and FCR market bids are both assumed to be fully accepted (i.e., bidding at 0 €/MWh).
- The considered asset is supposed to act as price-taker, hence it does not report effective changes on the market
- The battery system is assumed to make predictions before the market closure, which is usually a day before the real-time transaction. In particular, for DAM, the Gate Closure Time (GTC) is at 12.00h every day, while for FCR, the GCT is every morning at 8:00h and creates bid for the six blocks of four hours in the following day

In the following section, a zoom-in on Dutch electricity prices is outlined. The Netherlands is the reference country in this thesis, while German data are only used for comparison.

4.1.2. Dutch Day-Ahead Market Price Analysis

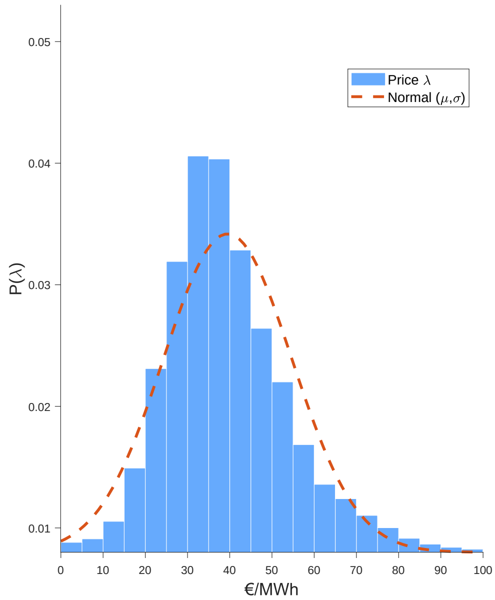
Since the outcome of the business case is strictly dependent on the market prices, an accurate price forecast for an electricity market has a definitive impact on the bidding strategies by producers or consumers [53]. Firstly, data analysis on the power market values has been conducted. Market prices can be interpreted as time series components, where the systematic components represent the consistency or recurrence and can be described and modeled [53]. A given time series should consist of three systematic components (level, trend, seasonality) and one non-systematic component called noise. The collective day-ahead markets data with 24 hourly reference periods and a cover of 4-year rolling period from 1 January 2016 to 31 December 2020 has been evaluated. The Prophet function [54] available in Python was used to ease the data visualization. This function uses a decomposable time series additive model with three main model components: trend, seasonality, and holidays as described in (4.1) below [54]:

$$y(t) = g(t) + s(t) + h(t) + \epsilon \tag{4.1}$$

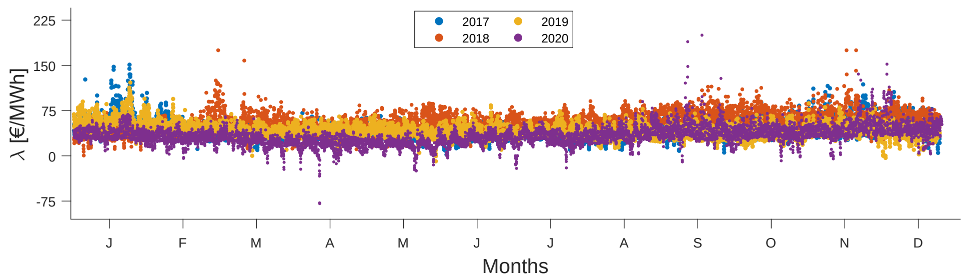
Where $g(t)$ represents the trend function which models non-periodic changes, $s(t)$, instead, constitutes periodic changes (weekly and yearly seasonality), and $h(t)$ is the effects of holidays which may occur irregularly over one or more days. The noise term ϵ represents any changes not accommodated by the model. An additive model is linear, where the exact quantity consistently makes changes over time. The Prophet function was preferred since it provides easy data handling and manages a larger quantity of data than the *statsmodel* Python library.

Data Visualization

The first modeling step is to carry out an initial transformation on the data. Looking at the normal distribution of the values in Figure 4.1a, several observations can be made. Firstly, there seem to be long thick tails and significant outliers. Secondly, although not a strict condition for a linear model, the distribution seems slightly positively skewed, with longer tails on the right side (high prices). Median and mean values result 39.5 €/MWh and 38 €/MWh respectively, while the standard deviation is 15.23. Standard deviation measures the dispersion of a dataset relative to its mean. Generally, a volatile price has a high standard deviation (σ_{STD}). Its value fluctuates for every single year, with 2018 and 2020 marking the highest σ_{STD} of 15.5. Figure 4.1b provides the evolution of the DAM prices for each sample along the year. It highlights how 2018 has the highest values and 2020 the lowest.



(a) Histogram of normalized historic dutch day-ahead market data (2016-2020)



(b) Scattered plot of the DAM market price plotted in a single year roll-out

Figure 4.1: Historic Day-Ahead Market Data Prices from 2017 to 2020. Monthly trend for each year

Therefore, to have a more precise overview, daily resolution data plotting has been performed. In this way, many outliers are avoided without damaging the quality of the representation. Figure 4.2 shows the fit of the spot market prices data with 24h resolution. The red line captures the time-series

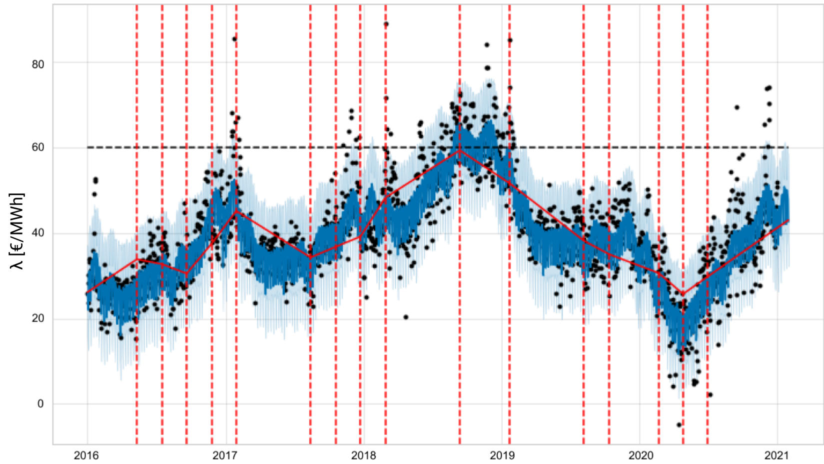


Figure 4.2: Daily electricity market data fitting from 2016 to 2021 (Netherlands). Segmented red line represents the trend. Vertical dashed red lines mark the trend change-points. Black dots mark the outliers

trend, while the vertical dashed red lines mark its change-points. The algorithm catches the non-systematic component marking them as black dots. The main reason for the electricity price spike concerns matching supply and demand on a second-by-second basis. Other reasons could be identified in [55]:

- Volatility in fuel price;
- Load and Generation uncertainty;
- Congestion of Transmission line;
- Last call decisions of a market participant;
- Market manipulation (market power, counterparty risk).

In particular, since the energy outlook for the Netherlands is majorly signed by natural gas, an increase in fuel prices leads to increased price volatility.

As said, the Prophet function helps to decompose the time series using the additive decomposition method. Shifting attention to a zoomed-in version of the original time series, visible in Figure 4.3, additional information can be obtained. Clear seasonal patterns can be observed, both yearly, weekly, and daily.

The vertical axes are label according to the additive trend for each seasonality. As known from the literature, the most distinct property of electricity price is its volatility which measures the change in the price value over a given period. Mathematically speaking, it can be computed as the standard deviation of percentage change in the daily price against a broader seasonality (weekly or yearly) [55].

In Figure 4.4 the trend is also depicted for better visualization and holiday trend. Comparing it with the yearly trend of Figure 4.3 it can be observed that the highest prices occur in the winter period, whereas the price drops in spring and slowly rises again from July to October. According to the Dutch bank holidays calendar, a positive correlation is expected only for Good Friday and Easter Sunday, while, as expected, the highest drops occur during Easter Monday and Whit Monday (Figure 4.4).

Even though the electricity price is becoming more and more volatile, especially in the Netherlands [56], it is not regarded as random. Hence, it is possible to identify specific patterns and rules on market

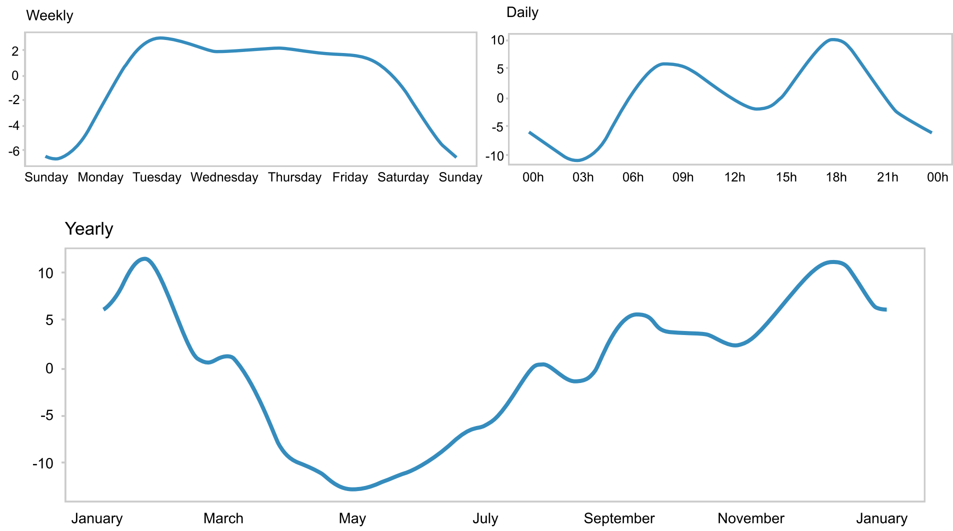


Figure 4.3: Weekly, Yearly, Daily decomposition of day-ahead market data.

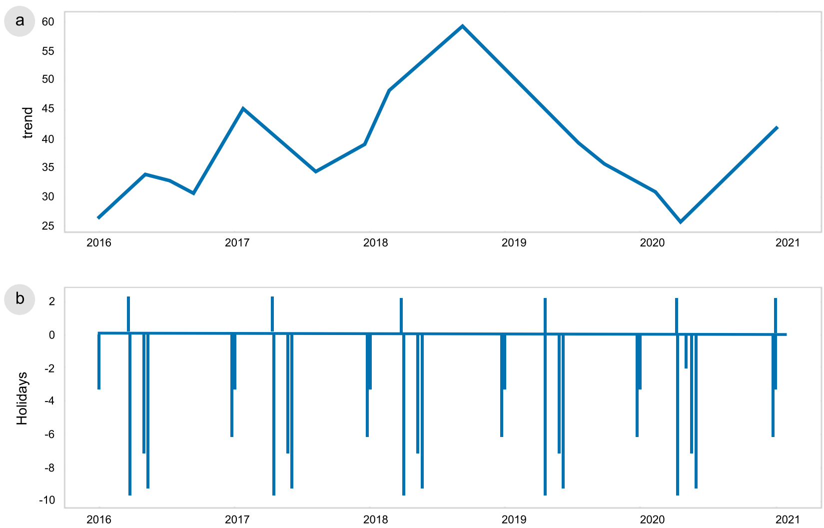
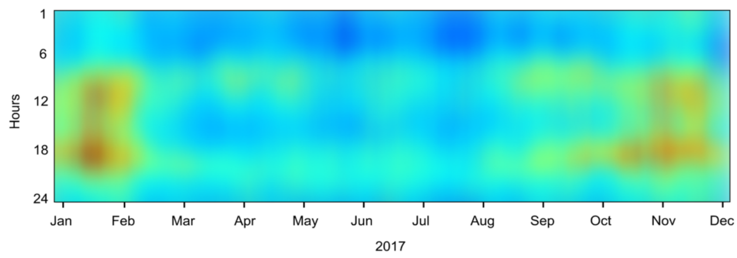
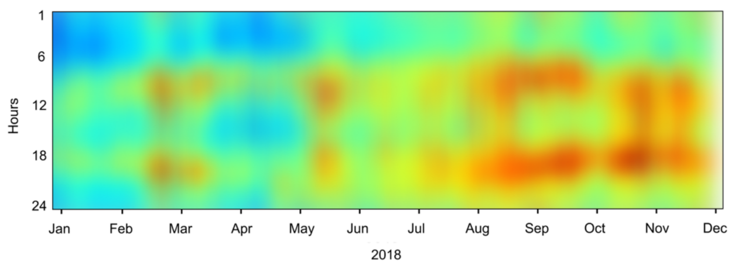


Figure 4.4: Fig. a) shows the trend that the prices have followed from 2016 to 2020. Fig. b) displays the holiday trend according to the dutch bank holiday calendar for each year. The first drop is 1st of January as New Years Day it follows Good Friday, Easter, Easter Monday, King's Day, Ascension Day, Whit Sunday or Pentecost Sunday, Whit Monday or Pentecost Monday, Christmas Day, and Second Christmas

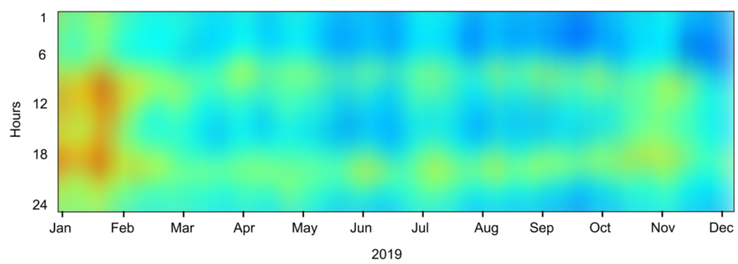
volatility. For instance, the weekly pattern proves the decrease in demand during the weekends, with Saturdays still relatively high due to the typical Saturday night pick price. In contrast, the daily pattern proves the drop in price at night due to lower demand and relatively high inexpensive wind output (market bid around zero marginal price). In the morning, there is a strong peak and during the day the price levels off only to increase again for the evening peak. This midday leveling off is among other things a combination of inexpensive solar output rising, along with the effect of many people residing together at work, reducing household demand. Such patter is also confirmed in Figure 4.5 where the warmer colors appear, along the years, right before midday and around 8 PM. On the other hand, on average during the night there is a substantial decrease. From these initial observations, it seems reasonable to hypothesize that seasonality and exogenous variables like aggregate demand and aggregate intermittent renewable output may impact the price.



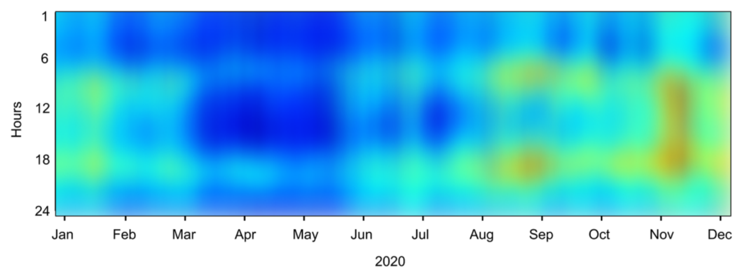
(a) Dutch day-ahead market 2017



(b) Dutch day-ahead market 2018



(c) Dutch day-ahead market 2019



(d) Dutch day-ahead market 2020

Figure 4.5: Heat-maps of dutch electricity prices from 2017 to 2020. Warmer colors indicate higher prices. The cap price is set to 100 €/MWh and floor price to 0 €/MWh.

Moreover, the trend showed in Figure 4.1b and Figure 4.5 confirms what has been pointed out from TenneT reports. In 2018 is registered the highest average price with an increase of 33% from 2017 primarily due to increasing fuel- and emission allowance prices [50]. In Figure 4.5d is strongly visible the net influence of Covid-19 measures applied to the dutch industries(half March-end May), where supply and demand did not match for many recurrent hours, which has caused several negative market prices.

4.2. Construction of Day-Ahead Electricity Market Price Forecast

At first, the following research question *Which modeling framework is better for electricity price forecasting?* and *Which model is better across all hours, seasons of the year, and markets?* are used to drive the methodology applied. However, the scientific answer to these questions is out of the scope of the thesis. Hence just a brief introduction about the methods will be given.

In general, there are very few and minimal studies in the electricity price forecasting (EPF) literature where several frameworks are compared [57]. According to [58] the forecasting accuracy depends on two aspects. The first one is the expression of the forecasting problem, i.e., the logic and maths that determine how complex and intricate the modeling will be. At the same time, the second aspect concerns the adopted forecasting method, which is application-dependent. As the goal is to focus on the explanatory power of the past DAM prices, "pure price" or "price only" models have been considered. These models do not include exogenous (stochastic) variables such as weather, load, or renewable energy generation forecasts. The existing literature drives the choice of the forecasting models on short-term and long-term EPF and the desire to perform a comprehensive study that addresses the business case of BESS at DS level in a near-future scenario.

4.2.1. The Literature Review

Because of many complicated factors affecting electricity prices, accurate price forecasting turns out to be hard to achieve. Different methods exist for forecasting electricity prices, the authors of [57] and [58] conduct an extensive empirical study on EPF to address the optimal model structure for EPF by taking into account several modeling frameworks. While [59] classifies them into three groups. The first group is based on game theory, including Nash equilibrium, Cournot model, Bertrand model, and supply function equilibrium. These models focus on the modeling of strategies of market participants in order to find an optimal solution. The second group is based on simulation methods, which aim to mimic the dispatch of generators in the system based on its physical state within its physical constraints. The third group consists of time series methods, which utilize past behavior of price series combined with explanatory variables to forecast future prices. The main disadvantages concern the requirement of linearity and stationary of the dataset.

Among all, Auto-Regressive Integrated Moving Average (ARIMA) models have already been intensively applied to forecast commodity prices such as oil or natural gas [53]. The advantage of these methods is the simplicity and explicitness of their model structure and the proven accuracy of their predictions. ARIMA is a forecasting procedure consisting of autoregression (AR), integration (I), and moving average (MA) utilized to analyze and forecast time series data [53]. According to [58] an ARIMA-based forecasting model, based on historical electricity prices, could be used to predict future ones, where the model should be updated throughout time to maintain a relatively good accuracy using the closest electricity price data. Modelling-wise, ARIMA is a class of models that shows a given time series based on its past values, as its lags and the lagged forecast errors, so that such equation can be used to forecast future values. Assuming the electricity prices time series the (4.1) can be reformulated as (4.2):

$$P(t) = f(t) + g(t) + \chi(t) \tag{4.2}$$

The parts of Pt are: f(t), the non-periodic increasing trend, g(t) the periodic change trend, and $\chi(t)$ a stationary stochastic process reflecting the random fluctuation of electricity prices [58].

Furthermore, electricity prices are biased by seasonality components, as mentioned in subsection 4.1.2. Due to its structure, the ARIMA model cannot handle the seasonality present in the time series. The Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model extends the ARIMA mentioned above model taking the seasonality present in the time series into consideration. The SARIMA model has been widely used for forecasting the seasonal non-stationary time series. Therefore it is applicable for the data set input considered in this thesis [60]. The overall depiction of the modeling terms in the SARIMA models are seen in (4.3):

$$\textbf{SARIMA} \quad \underbrace{(p,d,q)}_{NonSeasonalPart} \quad \underbrace{(P,D,Q)_m}_{SeasonalPart} \tag{4.3}$$

where the uppercase notations is referred to the seasonal parts of the model and the lowercase one for the non-seasonal parts. In particular, the parameters are as follows:

- *p* and *P*: indicate the number of auto-regressive terms (AR)
- *d* and *D*: indicate the order of differentiation needed to ensure a stationary series
- *q* and *Q*: indicate the number of moving average terms (MA)
- *m* represents the number of periods per season (i.e the frequency of the time series)

4.2.2. The Proposed Hybrid Method

This section has presented the description of the proposed hybrid model together with general statistical methodology. Since the goal is to obtain a forecasted hourly data for an entire year and the precision of any forecasting method is usually in terms of months [60], a hybrid approach has been proposed to scale down the data from week to hour forecasting. The general scheme is as follows:

1. A class of models is formulated and identified for the observed data with certain hypotheses. The model parameters are estimated and weekly data forecasted are obtained
2. The model is ready for forecasting, the second class of model is evaluated to narrow the scope from week to hour.
3. Whether the hypotheses of the model are validated, the confidence interval estimation is performed.

Step 1

According to [61], the ARIMA models that have been already applied for price forecasting are usually quite simple or containing a small number of observations (i.e., three weeks data up to one year). In this thesis, the original data set has four years of hourly data, which results in almost 43 thousand data. Since such a dataset is computationally tough to handle, as studied in section 4.1.2, rich of outliers, a weekly price approximation has been used. Moreover, a detailed forecasting analysis is out of the scope of the work, hence the computational aid of the built-in Python function *auto.arima* has been used as the first attempt to seek the best fitted SARIMA model. In the end, a grid search is carried out, choosing a model by adjusted AIC (AICc) to select the final model components. This search provided a SARIMA model with specification $(3, 1, 1)(1, 1, 1)$, meaning 3 AR, 1 MA, 1 seasonal AR, 1 seasonal MA component, and 1 order differentiation are included in the model.

Step 2

Once weekly forecasted data are attained, the ARIMA approach has been extended to make daily market-clearing price forecasting in electricity spot markets. As claimed by [62], the volatility effect and intraday price jumps are essential factors to determine accurate price forecasting and to outline a business case. In order to achieve that, seasonal daily spread values for a rolling time of 4 years are evaluated. The forecast of the new dataset has been performed following Step 1. Secondly, the cap and floor price for each day of the year is obtained by integrating the daily spread of each season with the weekly price. Finally, the daily decomposition of Figure 4.3 is used as a reference to extract the hourly pattern.

Step 3

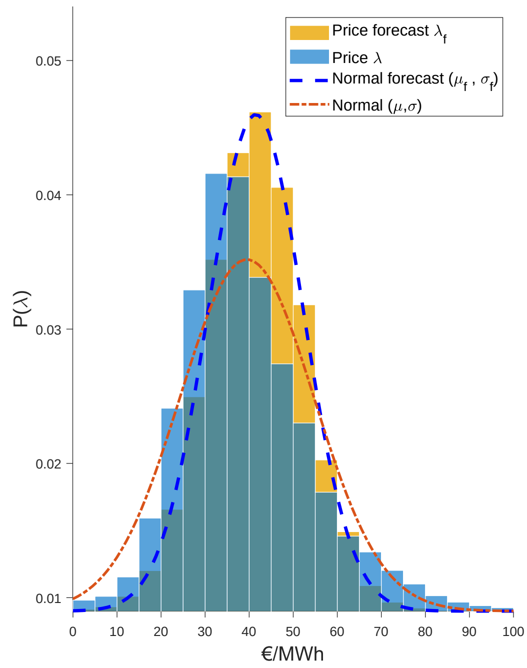
In this final step, the error correction and the confidence interval estimation are performed. Firstly, a benchmark hourly data set is estimated starting from the forecasted SARIMA weekly time series. In order to narrow the scope in hourly data, the additive forecasted Prophet trend is used as a reference. In fact, while computing the Prophet function, forecasted datasets are obtained. Such dataset has accuracy in the order of months. Therefore the confidence interval massively expands along the year [54]. The Prophet Weekly and Daily trend are used to extract the final dataset. The hourly residuals value is calculated by comparing the data obtained in Step 2 with the one mentioned above. In the end, residuals values are used to layout the confidence up and lower band. As a consequence, 3 cases are shaped and tackle in the next chapter.

Reflection

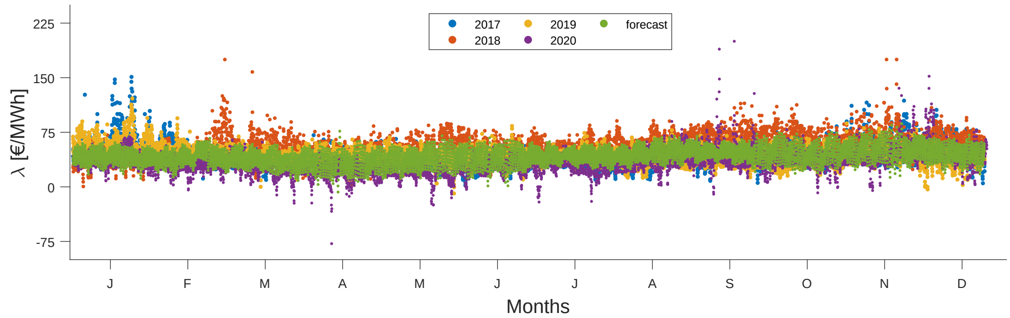
In Figure 4.6a the forecasted DAM prices together with the historic one are displayed. Median and mean are shifted towards higher prices rising to 41.5 €/MWh and 41 €/MWh respectively, while the wings of the normal fit curve result more flatted, concluding that spot prices will have a positive growing trend according to the forecasted method used. The σ_{STD} of 10.2 is also lower than the historical data average one and the shape fits better a normal distribution. Although such positive correlation, higher average prices are not a synonym for higher revenues. As a reference, Figure 4.6b shows how the forecasting algorithm has formulated less outlier with a higher concentration of values around the mean.

Unfortunately, the forecast generated model cannot be compared to forecasts from other methods reported in the literature as the comparison with other methods is left out of scope. Furthermore, the performance of other methods cannot be compared to the method applied, as market conditions differ strongly between markets and periods. Although no comparison is made, the method introduced shows to be able to forecast all relevant price series, which form a valuable basis to be used in the future scenario. Moreover, classic forecasting validation as Mean absolute deviation errors (MAD) and mean square error (MSE) cannot be used since the accuracy of forecasts can only be determined by considering how well a model performs on new data that were not used when fitting the model. This is not the case due to the hybrid proposed method. Additionally, the size of the residuals is not a reliable indication of how sizeable actual forecast errors are likely to be.

The structure of making a reliable forecasting method is also left out of the scope. As mentioned, nowadays, reliable methods concern short-term price forecasting. The goal was not to develop a forecasting tool but rather to create scientific-based forecasted price data to use in the case study.



(a) Histogram of normalized of historical and forecasted wholesale market prices.



(b) Scattered plot of historical and forecasted wholesale market prices.

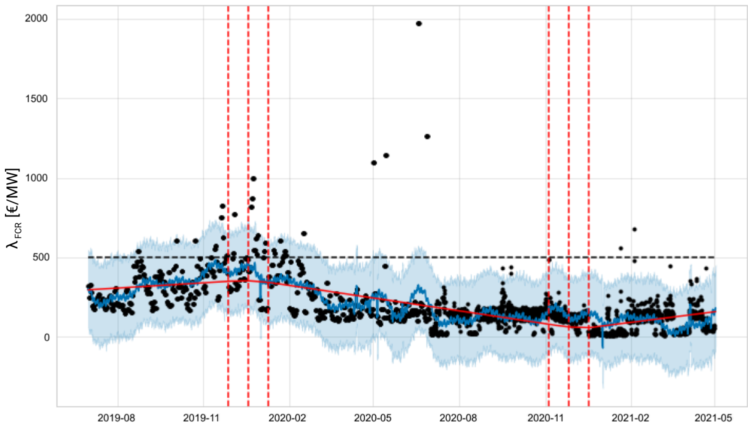
Figure 4.6: Historic Day-Ahead Market Data Prices from 2017 to 2020 and forecast data profile. Monthly trend for each year.

4.3. FCR Price Analysis

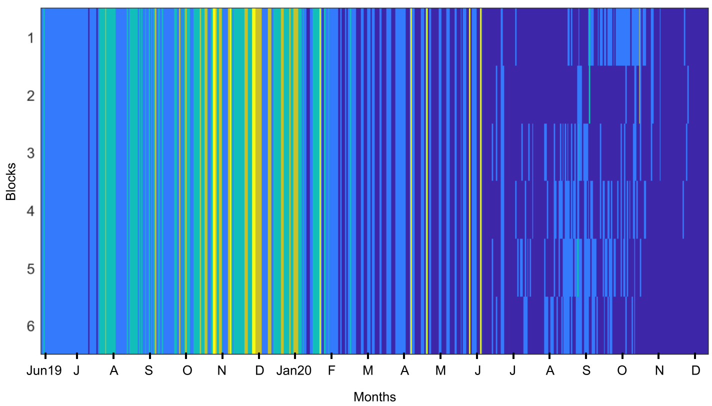
As mentioned in chapter 2, the Continental Europe grid has three categories of reserves, respectively, frequency containment reserves (FCR), frequency restoration reserves (FRR), and replacement reserves (RR). In countries like Germany and the Netherlands, a market has been set to secure sufficient FCR volumes. Moreover, due to the technical requirements of FCR, the potential providers are usually fast power generators (i.e., fire gas power plants) or hydro generators [34]. As a consequence, in some countries like the Netherlands, the FCR price has increased. This price increment encourages the evaluation of other solutions for providing these reserves, such as BESSs.

From Figure 4.7a the number of outliers stands out, remarking that FCR prices have recently increased, benefiting BESS owners. However, the lack of data does not help to have a complete visualization for a roll-out of several years. It is notable that prices have varied considerably around their means and that the average price is already quite significant (i.e., 240 €/MW or 60€/MW/h). The price distributions of such ancillary services are highly negatively skewed, with median prices below the mean and occasional high spikes of values far exceeding the means.

From the heat map of Figure 4.7b is hard to visualize a recurrent pattern, unlike wholesale market prices of Figure 4.6a. Nevertheless, it is considered to point out how the prices strongly reduce after July 2020. Such event could be a direct consequence of the fact that until July 2020, the FCR market was split into daily delivery periods. Only starting from July 2020 on-wards, price data for the Four-hour blocks are being published. Prices became more volatile after the introduction of daily auctions in 2019. From Figure 4.7b it is also visible that intraday price spike does not occur often. However, the Dutch market often has the highest prices for the 9-12 and 17-20 hour blocks. Unlike energy arbitrage in this market, the revenues will be more driven by the high average price than its volatility. Therefore, prices for FCR behave very differently compared to DAM prices, which are usually higher when consumption is high. Among the factors that influence the price, since natural gas plants generators account for most FCR provision, aspects affecting these resources are likely to influence the FCR price. Moreover, day-ahead wholesale electricity price is also correlated with FCR prices related to the opportunity cost for a producer to deviate from its optimal output level to provide FCR [34].



(a) FCR prices roll-out. Segmented red line represents the trend. Vertical dashed red lines mark the trend change-points. Black dots mark the outliers



(b) Heat-map of FCR prices. Warmer colors indicate higher prices. The cap price is set to 800 €/MW and floor price to 50 €/MW.

Figure 4.7: Historic Primary Frequency Regulation (FCR) Data Prices of the Netherlands from June 2019 - April 2021

4.4. The Fast Charging Station Model

In this case study, all three modules presented in Figure 3.1 Wholesale Market, Primary frequency regulation, and DSO operation will actively exchange information.

In chapter 2 the primary use case of a battery operating in the distribution grid is listed. As mentioned, Distribution System Operators (DSOs) are nowadays facing new technical challenges, principally due to the unpredictable nature of renewable energy generation assets (above all, solar and wind power) and of Electric Vehicles charging stations (EVs) [12]. Those are stochastic factors that are hardly penetrating in European distribution grids and especially in the Netherlands. The goal of the second case study is to evaluate the business case for BESS in DNs. This is done by assessing the proposed optimization model and partially answer the research questions:

- How can we model the BESS market participation and DSO operation in an optimization problem?
- What is the technical impact of the BESS, and what are the revenues streams at DS level?
- How much is the RES asset owner saving from the grid connection thanks to the storage system? And the DSO benefit?

The answer to the first research question was already partially introduced while evaluating the model performance in section 3.3. How the before-mentioned block parameters are calculated will be shown in the following sections. The technical impact and the economic benefits are also introduced, but the complete answer will be provided in the next chapter.

4.4.1. Case Study Description

These sections aim to describe the environment for the second case study. The layout is composed of a Photovoltaic (PV)- Fast Charging (FC) station equipped with a BESS of a third-party owner since DSO is not entitled to own a storage system. An existing reference environment of a PV-FC station in the Netherlands has been selected.

The simulations are carried out using demand profiles extracted from energy measurements taken at four stations in the Netherlands for the whole of 2020. These measurements were performed for a year roll-out at a sampling frequency of one minute. The task intended for the BESS is to perform peak-shaving on the EV demand and renewable firming and self-consumption on the solar plant in order to restrict the grid-tie power exchange.

A detailed explanation of the electrical connection of the system is not relevant for the study. The system layout investigated in this thesis includes DC fast charging stalls for a total power of 250kW, a 500 kW solar system, a 500kW 1C BESS, and an LV/MV transformer that couples the station to the MV grid. For visualization, the sizes and components are also displayed in the table below:

Table 4.1: System components of the PV - FC station case study

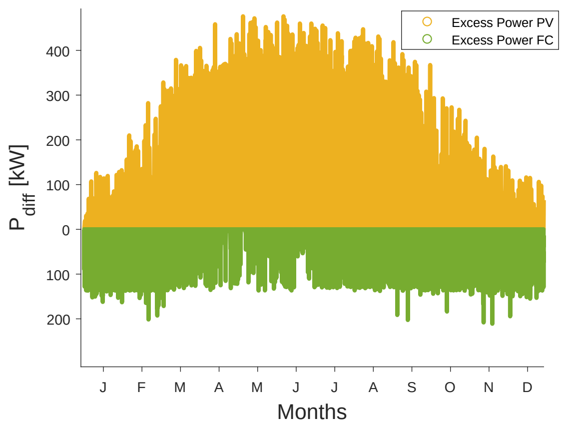
System Components	Size Specification
BESS	500kW / 500kWh
Solar Sytem	500 kW
EV Charging station	250 kW

4.4.2. Peak Shaving Evaluation

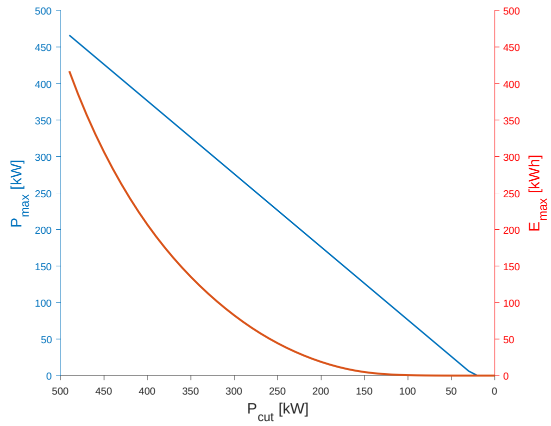
The first step is to identify the DSO's recurrent schedule requiring the battery for its operation. Therefore, "step zero" is to evaluate the model "block time-steps" to reserve battery running hours and capacity to accomplish such secondary operations. The methodology applied is as follows. At first, the data are extracted for a rolling period of 1 year (2020) with 5 min timestep. It has followed the evaluation of PV power production and FC demand and identification of the optimal peak power to be shaved.

From Figure 4.8a the oversizing of the system is noteworthy. The double size of the solar system compared to the FC station is seen in the above zero part of the graph, where a typical sun power curve with peak production of 480kWp is displayed. Despite that, the EV load is still relatively high throughout the year, with the values evenly distributed around the mean of 40 kW, with a peak load of 220kWp. It can be concluded that there is no perfect timing between the necessity of charging the EV and the power produced by the PV plant, with excess in both directions, which foster a battery system integration.

Figure 4.8b shows how peak shaving can be performed and the corresponded Power and Energy that can be saved according to the amount of power curtailed (P_{cut}). The power of the PV-FC station (P_{max}) has a linear dependence with P_{cut}, whereas the its energy (E_{max}) and P_{cut} are inversely proportional.



(a) PV-FC charging station power trend. The orange area above zero represents the excess power produced by the solar plant, while the green area is the extra power demand due to EV charging



(b) Comparison power and energy saved according to the amount of power curtailed. In blue on the left-hand side the power and in red on the right-hand side the energy

Figure 4.8: PV-FC charging station power trend for a year (2020) and peak shaving selection

Furthermore, it is relevant to mention that the power shaving will be performed both on the power injected into the grid due to PV overproduction and on the power extracted from the grid due to demand charging. As a direct consequence of the curtailment, the DSO would benefit from relieving the grid from some obstacles, such as peak demand and line congestion. For this service, the BESS owner would ask the DSO to be remunerated. A proposed framework will be investigated in section 5.3.1.

As mentioned in section 3.3 the parameters P_{block} and SoC_{block} have to be extracted to be implemented in the optimization algorithm. Hence, after having investigated the excess of power, the respective energy needed is examined. Such values are rationalized with the battery nameplate capacity (500 kWh in this specif case), and the SoC_{block} is defined. The P_{block} instead is a direct result of the shaving.

Additionally, in the absence of information about the congestion management of the grid, peak shaving will be outlined following the reduction of revenues that the DSO operation blocks generate compared to whether they are not taken into account. Several cuts have been performed to achieve the optimal compromise between revenues and technical aid to the DSO and the PV-FC station owner. In Figure 4.9 the drop of profit depending on the power shaved is drawn. This reduction is the outcome of the amount of timestep blocked by the P_{block} and SoC_{block} parameters. During the simulations, the inputs parameter concerning the number of cycles in the DAM and FCR market was kept equal. Besides, the figure displays that an optimal outcome, with less than 5% of revenues losses, would mean shaving 20% of the PV power and up to 40% of the FC station intake.

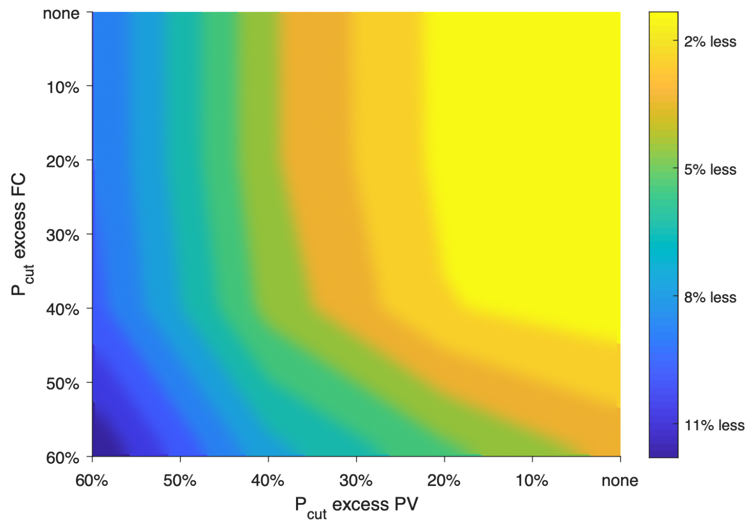


Figure 4.9: Revenues decrease depending on the power shaved from the PV-EV charging station

The aforementioned optimal output has been used as a reference example in Figure 4.10 to show which volume and how often the storage system will be called upon. It is worth highlighting how the solar intake is null during the wintry month while the FC station requests a continuous but lower power demand. The upper value represents the SoC that is added to the battery by the DSO to generate a deviation of the battery SoC, while the yellow value is the SoC that is requested to be kept by the BESS to be able to operate. The next chapter will assess the PV - FC station owner's economic benefit in terms of reducing the peak grid connection.

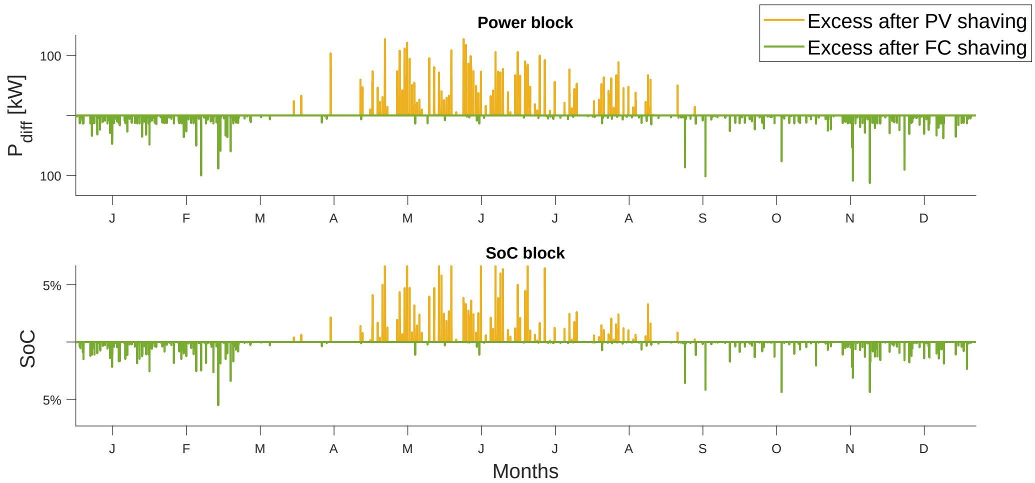


Figure 4.10: Example of Power block and SoC block profile obtained after have shaved 20% of the PV power and 40% of the FC station

5

Case Study Results

In this chapter, the complete results of the performed simulations are displayed. The aim does not consist of assessing the business case of a particular case study, however, to provide a "bigger picture" regarding the potential market that can be tackled, what are the possible drawbacks of BESS applications at the DS level, and what are the technical and monetary advantages.

At first, the financial parameters used to assess the results are explained. Secondly, the specific case study of a BESS operating in the electricity market is shown. It follows the second case study where those performances are compared to when also DSO services are taken into account. A Fast Charging station environment is considered, which data have been evaluated in section 4.4.2. Finally, BESS lifetime considerations conclude the chapter.

5.1. Financial Analysis Factors

The capital costs of Li-ion BESS include both the battery pack and the Engineering Procurement Construction (EPC), which concerns the installations part. As introduced in chapter 2, the hardware of the battery can be subdivided between DC and AC components. The DC system is the cells, modules, packs, DC converters, BMS, and internal battery cabling, whereas the AC system can be identified in HVAC, inverter, transformer, and AC cables. The BESS capital expenditures ($CAPEX$) corresponding to the DC system have been declining during recent years, going close to 350 €/kWh, with expectations to further drop reaching 250 €/kWh in 2025 [63]. Thus, the overall BESS cost could lie around 400 €/kWh.

A project owner must evaluate an investment decision from several points of view. Financial indicators of the investment form the core part of this decision. Therefore, it is essential to understand the project assessment strategy of investors. When investors evaluate project opportunities, they have different expectations regarding the project value based on their alternative investment opportunities. Thus, providing an appropriate financial evaluation of the project is essential to attract potential investors. Below the most common and significant factors and their calculations are listed for financial decision-making.

Net Present Value

The difference between a project's value and its cost is its net present value (NPV) [64]. The formula is shown in (5.1) below, where C_t is the cash flow at year t and r the discount rate:

$$NPV = C_0 + \sum_{t=1}^{n} \frac{C_t}{(1+r)^t} \tag{5.1}$$

As a general rule, project managers can best help their shareholders by investing in projects with a positive NPV and avoiding those with a negative NPV.

Internal Rate of Return

Instead of calculating a project's NPV, project owners can also compare the expected rate of return from investing in the project with the return rate that shareholders could achieve on equivalent-risk investments in the capital market. Projects become attractive that provide a higher return rate than what shareholders could earn for themselves [64]. If applied correctly, the rate of return rule shall always identify projects that could increase value. The Internal Rate of Return (IRR) is defined as the discount rate that makes $NPV = 0$ [64]. So it can be calculated by applying the NPV calculation rule on the investment for the project lifetime and find the discount rate where $NPV = 0$.

Payback-time

Generally, a project's payback time is defined as the number of years it takes before the cumulative discounted cash flow equals the initial investment. The payback rule states that a project is viable if its payback time is less than some specified cut-off period. However, in the energy sector, an investment shall be evaluated based on comparing the energy generation costs with and without the new investment. Thus, it is not a simple payback calculation, but a net cumulative discounted cash flow calculation as shown in (5.2) [64]:

$$NPV = C_0 + \sum_{t=1}^{n} \left(\frac{C_t}{(1+r)^t} - \frac{C_{base_t}}{(1+r)^t} \right) \tag{5.2}$$

In order to effectively use the payback rule, an appropriate cut-off period has to be determined. If the exact cut-off time is chosen regardless of project life, it will prioritize many poor short projects and reject several good long ones. Thus it can affect the quality of the project [65]. For BESS applications, the determined cut-off period differs case by case, but overall, in the energy sector, it can be stated that if the payback time is lower than the project lifetime, the investment shall be considered since it results in an overall cheaper energy production [66].

In addition to the aforementioned financial parameters, four factors are taken into account in the evaluation of the results:

- revenues based on market applications
- number of battery cycles
- time spent in DAM and procuring FCR
- number of DSO activations

5.2. Operating a BESS in Electricity Markets

The first case study analyzed concerns about operating a BESS in the electricity markets, performing energy arbitrage, and primary frequency regulations. This section will validate the basic mathematical modeling of the deterministic optimization model that coordinates multi-market trades for a single BESS plant. The comparison of the results between the different strategies and inputs applies the price-taker analysis. That means that the revenues for all optimized bids are computed using the method from chapter 3, which assumes that the price does not change as a result of a change in strategy. As mentioned in chapter 4, the understanding of market data is fundamental to drive the comprehension of the results due to the price-driven optimization function. In this section, DAM and FCR market prices of 2020 for the Netherlands are used. This case study makes only use of the market modules without using any DSO operation block. The input data of such scenario are gathered in the table below Table 5.1 in which battery and optimization modules specifications are illustrated.

Table 5.1: Model inputs for first case simulation

Battery Specification	Modules Used
P_{rated} 500 kW	Wholesale market
E_{rated} 500 kWh	Primary frequency regulation market
η_{rtp} 90%	

As already mentioned in chapter 3, the model inputs can be customized accordingly to the specific type of battery system chosen. In the following cases, a generic Li-ion technology with an overall system efficiency of 90% is considered, while no degradation was considered to simulate the battery response for every new hourly timestep for one year. Moreover, a BESS rated 500kW/500kWh has been considered, assuming that the BESS is aggregated with other BSPs clustering together up to 1 MW to procure FCR.

5.2.1. Model Results for 2020

The results are evaluated in terms of yearly revenues, time spent online in each market, and complete battery cycles. The first set of results is shown in Table 5.2.

Table 5.2: Model Results of a BESS operating in the Netherlands in 2020. (a) marks the results when double bid constraint is binding

	DAM	FCR	DAM[a]	FCR[a]
Revenues [€]	3850	76500	3100	76000
Activations [h]	410	1860	240	1850
Cycles	233	-	200	-

At first glance, the considerable amount of revenues that primary frequency application leads in contrast with only performing energy arbitrage stands out. Thus, it confirms what has been stated in the literature that European wholesale market prices might not be high enough to deem energy arbitrage as the only revenue stream. However, as evaluated here, FCR having a high power to energy ratio turns consequently attractive for battery energy storage, especially for 1-hour batteries. Despite the high revenues, the number of activations is also noteworthy. Simultaneous participation in DAM and FCR markets occurs 320 times a year. Overall, when the constraints (3.16) and (3.17) are not enforced, and a double bid is allowed, the BESS is online for 1946 h/year, which corresponds to slightly more than 20% of the year.

On the right-hand side of Table 5.2, constraints (3.16) and (3.17) are biding, thus results in a general drop of the outcome figures. From a lower number of DAM, activation follows a decrease in the revenues. Even FCR revenues drop since the SoC level probably excluded the possibility of performing FCR for the following settlement period. Constraints (3.11) and (3.12) are consistently enforced, and the possibility to do not perform energy arbitrage during FCR commission exclude several hours where the BESS can exploit additional revenues. However, online and idling time is comparable to the results mentioned above. This first group of results deduced that the simultaneous operation is more profitable and does not intensively affect activations. Therefore it will be used to display the whole next group of results. However, as a limitation of the model, in order to limit the power output (see (3.18)), the DAM and FCR bid cannot be made at max power, even though, in reality, it might happen that in a specific time slot the asked regulating power is lower and therefore a higher DAM operation could be assessed.

5.2.2. Future Scenario

In this section, the forecasted DAM prices elaborated in chapter 4 are used. As mentioned, three possible elaborations have been investigated to shape upper and lower boundaries for the forecasted dataset. On the other hand, forecasting mechanisms have not been applied to FCR prices; instead, German prices have been used. The main reasons behind this choice are the following:

- Lower data availability to train the model
- Higher uncertainty driven by the factors that influence such prices (i.e., gas price, grid expansion, integration of new European platforms)
- European tendency of FCR prices to decrease due to new green assets participating in the market such as BESS.

Furthermore, as studied in [15] and reported in Figure 2.4 of chapter 2, Germany has been highlighted as a country where BESSs are a mature technology exploited in procuring ancillary services. Therefore, it has been assumed that Dutch FCR prices will follow that direction, and German data are suitable for modeling the near future. The general outcome is displayed in Table 5.3 that shows the total revenues for the different strategies and forecasts.

Table 5.3: Model Results of a BESS operation in a forecasted future in the Netherlands.(1) marks the results obtained with the upper boundary of the forecasted price. (2) marks the results obtained with the lower boundary of the forecasted price

	DAM	**FCR**	**DAM**^{1}	**FCR**^{1}	**DAM**^{2}	**FCR**^{2}
Revenues [€]	4900	13400	3000	13500	2930	13450
Activations [h]	415	500	310	505	270	550
Cycles	310	-	225	-	220	-

The critical point of this group of simulations is the drastic drop in revenues in the FCR market by 70%. Its number of activation results almost a quarter than in 2020, while DAM participation actively increased. This trend can be explained as the direct result of much lower average prices in the FCR German market. On the other hand, the increase of the forecasted DAM revenues results from the higher daily volatility due to the forecasted methodology applied. It is also relevant to mention that the revenues using as input the lower and the upper boundaries of the forecasting dataset do not differ much considering the comparable number of activations. Instead, they are even lower than the regular forecasted one. Consequently, it can be stated that BESS catches profitability in the volatility of the price rather than its mean value. Besides, the highest profitability still lies on frequency applications, the Netherlands is currently a much higher paying market than Germany.

The division in three cases is also kept in the next paragraph, even though the difference is not crucial in draw conclusions.

5.2.3. Financial Analysis

This section will evaluate the result in terms of the financial parameter defined at the beginning of the chapter. As explained, three possible forecasted values have been outlined, original forecasted prices, upper boundary, and lower boundary. They will be reported as Case 1, Case 2, and Case 3, respectively. The input used to evaluate the results are displayed in the Table 5.4 below, where the BESS $CAPEX$ and $OPEX$ are obtained from [63] and [28]. As mentioned at the beginning of the chapter, the $CAPEX$ includes the cost for the Power Electronics Converter (PE) and the Balance of the Plant (BoP). The average inflation rate r in the Netherlands of the past three years holds around 2.5% - 3 %. However, in Europe, these values fluctuate quite a lot depending on the country [67]. In the table, 3.5% is reported, which is a more conservative value than what [28] assumes.

Table 5.4: Financial analysis input parameters. BESS $CAPEX$ and $OPEX$ and the interest rate r are obtained from [63], [28] and [67] respectively

	Decision Factors
BESS	500 kW / 500 kWh
CAPEX	400 $€/kWh$
OPEX	8 $€/kWh$
r	3.5%

NPV, IRR, and Payback are widely used in capital budgeting to establish which projects are likely to turn the most significant profit. In particular, the NPV is a method used to assess the current value of all future cash flows generated by a project, including the initial capital investment (CAPEX). In order to be able to perform the yearly cash flows, the inputs of Table 5.4 are considered. The outcome of the projected cash flow of a 500kW/500kWh BESS operating in electricity markets is represented in Figure 5.1 on an eight-year horizon. The positive flows are based on the revenues calculated with the 2020's dataset (in gray) and linearly scaled to the future outcome, which has been assessed as discussed in the section before. The single cash flow is based on the yearly revenues subtracted by the yearly O & M cost (8 €/kWh). The graphic visualization of the significant difference in the result marks, even more, the current high profitability of pursuing FCR application in the Netherlands in regards to Germany.

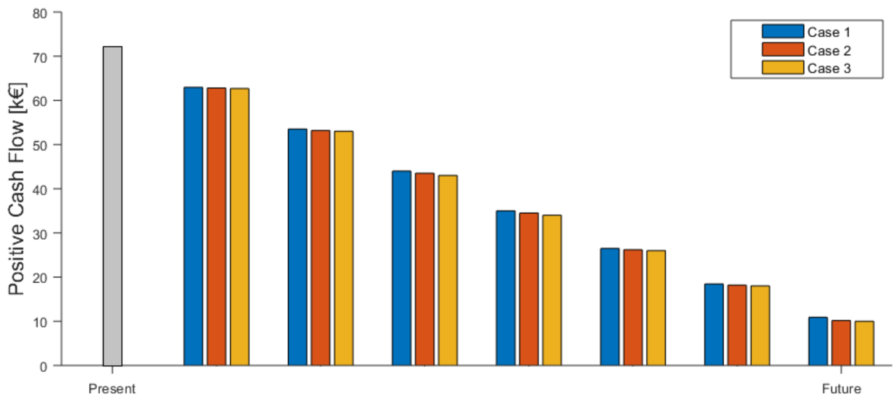


Figure 5.1: Projected cash flow of a 500kW/500kWh BESS operating in electricity markets. The revenues are based on the calculated 2020's one (in gray), scaled linearly to the future outcome. In blue the trend based on the forecasted dataset (Case 1), in red the trend based on the respective upper boundary (Case 2) of the dataset and in orange with the lower boundary (Case 3)

The result of the cash flows is assessed in Table 5.5. For the BESS owner, an investment is attractive if the NPV or the IRR is high, yet there are market segments that a successful outcome is predictable even with high financial values. Only market applications have been considered; hence, few decision variables affect the results. Companies predominantly use both NPV and IRR to evaluate investments. Generally, NPV provides more information about the expected return. Financial analysts also rely on IRR because IRR is more intuitive since it directly expresses the monetary advantages of such projects. The downside is that IRR does not address the scale issues, while the NPV already shows the magnitude of expected revenues. In conclusion, assuming the accuracy of the assumptions, this project will lead to an average of 125 thousand euros in 8 years, with the payback time reached after 3.2 years. For comparison, it has been estimated that the payback will be reached in more than 10 years by adopting German prices to run the simulation. Therefore, it would be even more essential to stack additional revenue streams to create an attractive business case.

Table 5.5: Financial analysis results of a 8 year horizon. (1) refers to the forecasted DAM dataset using the upper boundary of DAM prices while (2) with the lower boundary

	Case 1	**Case 2**[1]	**Case 3**[2]
Cycles year 1	233	233	233
FCR activ. year 1	465	465	465
NPV	130 $k€$	121 $k€$	120 $k€$
IRR	19 %	17 %	17 %
Payback	3.10 $year$	3.20 $year$	3.20 $year$

5.3. Fast Charging Station Model Results

In this third part of the chapter, the BESS discussed above is placed in the PV-FC station environment illustrated in subsection 4.4.2. This section aims to show and discuss the simulation results when all the three optimization modules are operating with double bidding constraints deactivated. For the graphic overview of the players involved, Table 5.6 displays the input considered in the evaluation of this specific case study.

Table 5.6: Model inputs for Fast Charging station simulation case study

Battery Specification	Modules Used
P_{rated} 500 kW	Wholesale market
E_{rated} 500 kWh	Primary frequency regulation market
η_{rtp} 90%	DSO operation

In section 4.4.2 of chapter 4, it has been highlighted how possible shaves of power could be performed on the charging station dataset available. In particular, it has been assessed that shaving 20% of the PV power and up to 40% of the FC station intake would lead to less than 5% of revenues losses regarding only market participation. Such peak shaving is defined as optimal compromise and would then be referred to as such along with the chapter. The Table 5.7 indicates the general outcome of this group of simulations.

Comparing it with the results of Table 5.2 a general increase in the number of activations and cycles is remarkable. This may be addressed to the unexpected block placed by the DSO by limiting the power output or changing the BESS state of charge. Furthermore, as stated by the optimal peak power shave definition, the decrease in revenues is minimal; however, the number of operations raised. Therefore, online and idling time result not only price-driven but also determined by additional input constraints. A comparable effect can also be noted in the ”future” part of the table. Here, three cases are depicted depending on the price input.

The ”DSO operation” label is not reported on the future-side of the table since considered an input parameter of the model, hence priority in the computational algorithm as seen in Figure 3.2. Such operations are defined as the number of hours in a year that DSO blocks the BESS state of charge or injects additional charge into the system. If considered on its own, such value does not seem relevant to the problem. However, it has much more impact whether considering its effect. In fact, 150 times per year, the SoC of the battery is not at the optimal level, but either additional operation has to be performed to set it back, or a limited amount of operations are possible if a part of it is reserved. Moreover, for the sake of comparison is worth mentioning that if a 20% additional power shave on the demand intake were done, it would have generated an overall SoC deviation of 1700 times in a year. However, the percentage of SoC blocked or deviated stays most of the time lower than 5% (see Figure 4.10); hence no consisted deviation is registered. Besides, the additional service offered increases the BESS's online time by almost 500 hours in a year, reducing the overall idling time by 23%.

Table 5.7: Model Results of a BESS operation coupled with a PV-EV charging station with the optimal curtailed power.(1) marks the results obtained in case 2. (2) marks the results obtained in case 3. The value reported among brackets (*) represents the actual extra activation due to DSO. (**) marks the SoC variation that such operations report

	2020			***Future***					
	DAM	**FCR**	**DSO op.**	**DAM**	**FCR**	**DAM^1**	**FCR^1**	**DAM^2**	**FCR^2**
Revenues [€]	3100	76000	*tbd*	3950	12850	3000	13000	2840	13000
Activations [h]	450	1850	650 (495*)	350	465	320	505	315	500
Cycles	240	-	150**	230	-	238	-	225	-

5.3.1. Assessment of DSO Remuneration and Financial Analysis

A key point of this case study aims to assess the possible extra revenue coming from the service offered to the DSO. This additional stream has to be stacked on top of the revenues based only on market application. However, as mentioned in chapter 2, DSOs currently are not entitled to own a BESS; therefore a third-party owner has to be involved in providing services. In general, some difficulties arise when assessing other use cases to stack the revenues since, in many electricity systems, no precise remuneration regulation exists. Hence, market regulations and structures will have to evolve to create revenue streams for service providers. This is also the case of the Netherlands, where transparently and robust tools have to be developed in order to concretely assess financial incentives for providing services like congestion relief for the grid and time shift in peak demand [68].

A possible framework is proposed in this elaborate to demonstrate the economic benefit provided by additional application stacking. It should be intended as a bilateral agreement between the BESS owner and the DSO. Its mathematical visualization is displayed in (5.3). Since the BESS relieves the congestion, minor frequency deviation would occur, and therefore fewer times also the asset will be online performing such service. Hence, first, the peak power (kWp) shaved each month P_i^{block}, i.e., the one injected in the battery, is calculated. Secondly, these values are multiplied for the respective month's average frequency regulation price $\overline{\lambda_i^{FCR}}$. Considering the optimal shaving explained in the section before, an additional remuneration of 2800 € is calculated. Speculation on such base value can be evaluated in order to increase the figure further.

$$\sum_{i=1}^{12} P_i^{block} \cdot \overline{\lambda_i^{FCR}} \tag{5.3}$$

The input considered to estimate the financial results are displayed in the Table 5.4. Comparing the cash flow of Figure 5.1 and the future side of Table 5.7, only minimal differences can be spotted. For this reason, the average of the three future prospects will be considered in the following sections. In particular, it will be referred to as Case A when only remuneration coming from electricity market application is examined, and as Case B when DSO operation is also considered.

In Figure 5.2 the projected cash flow of Case A and Case B are compared, where in red is highlighted the possible proposed extra revenue based on DSO service speculation. A comparable decreasing trend is registered here as well. Nevertheless, it is interesting to note that the projected annual profit increases compared to the base case only thanks to the additional revenues stream, and in the future will be become almost a third of the total forecasted profit.

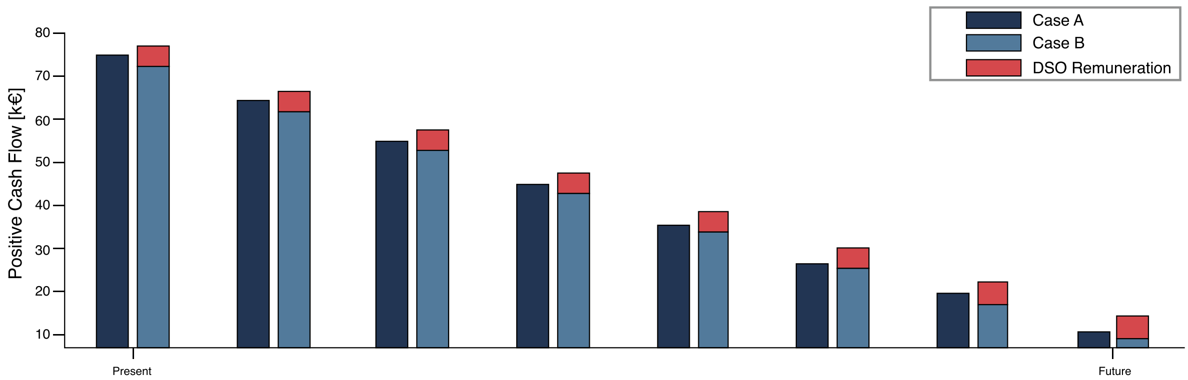


Figure 5.2: Projected cash flow of a 500kW/500kWh BESS operating in electricity markets and with DSO operation included. Case A indicates the cash flow coming only from market applications and Case B the cash flows with the DSO extra remuneration

In Table 5.8 the results in terms of the financial parameters are outlined. The table shows that the monetary return has improved by 5% and that the payback time reduced under 3 years. It could be concluded that additional remunerated services are beneficial from an investor's point of view. Although deviations from the optimal operation occur, the financial indicators display positive results.

Table 5.8: Financial analysis results comparison with DSO operation. Case A refers to when only market operation are considered, while Case B when also the DSO remuneration is taken into account

	Case A	**Case B**
Cycles year 1	233	243
FCR activ. year 1	465	465
NPV	125 $k€$	190 $k€$
IRR	18 %	23 %
Payback	3.15 $year$	2.90 $year$

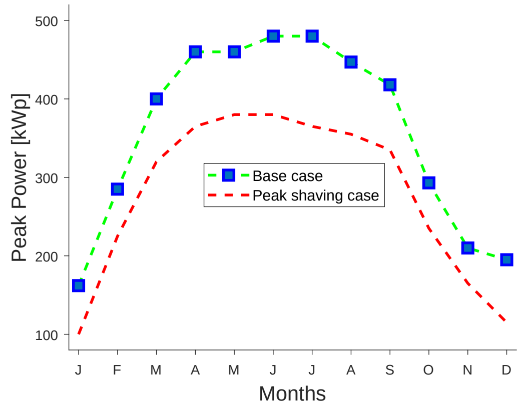
5.3.2. Assessment of the Benefit for the PV-FC Station Owner

Up to now, we have assessed the benefit for the DSO and the BESS owner. This section aims to estimate the economic benefit the PV-FC station owner will experience thanks to the BESS. The sizes of the system considered are reported in Table 4.1.

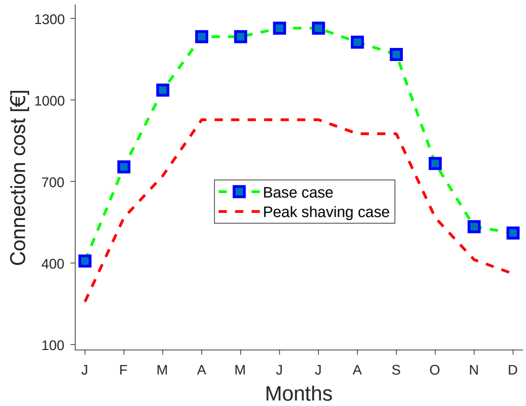
The BESS use case consists of BTM applications as peak shaving and load shifting on such a system. In Figure 5.3a a power shaving of 20% of the PV power and 40% on the FC station demand is applied. Thanks to that, the overall grid peak connection has been limited. In particular, a notable reduction is registered during the central months of the year due to the high power produced by the PV. It also results in a relatively higher shaving than during the year, where the grid congestion is mainly dominated by the EV charging demand.

Before properly evaluate the results of Figure 5.3b it is essential to mention that the cost of connection is based on the Stedin tariff of 2020 [69] in which the energy exchange costs are neglected. Furthermore, the contracted power is estimated assuming that the ratio with the monthly peak power does not exceed the 10% difference to avoid falling in additional penalties.

The relevant shaving on the PV production makes the cost curve flat during the year's central months. The trend leads to an overall 30% of monetary saving. In particular, from the simulation, the PV-FC Station owner more than 5000 euros a year on the peak power connection and around 3500 euros per year on the contracted power. It can be concluded that installing a BESS in such a case study is technical and economically beneficial. It is essential to mention that the benefit of a possible feed-in tariff of selling green power to the grid and other bilateral agreements in the act with the DSO are not considered since they are out of the scope of the analysis.



(a) Peak power grid exchange evaluation in normal condition (base case) and with BESS performing peak shaving



(b) Connection cost evaluation in normal condition (base case) and with BESS performing peak shaving

Figure 5.3: Monthly PV-FC charging station in base case and with peak power shaved of 20% of the PV power and 40% of the FC station

5.3.3. Capacity Fading Evaluation

As investors generally require different measures to evaluate their project opportunities, it is crucial to involve all these calculations to get an overall picture of a proposed energy system portfolio. Hence, to provide a complete vision of the results of BESS applications in distribution grids, the system's lifetime is investigated. The model simulates just a single year of operation, while in reality, the battery system will be operating for its entire technical life. The single year of operation will be used as a reference to evaluate the degradation of the cells. Furthermore, as outlined in [28], the power electronic wear is not particularly affecting the performance of the system itself. Therefore its evaluation will be considered as a prospect.

In this study, to assess the electrochemical cells lifetime, the empirical model for LFP (LiFePO4) batteries developed through accelerated cycling of battery cells and proposed in [16] is adopted. The equations together with some initial consideration are elaborated in section 2.6 of chapter 2. As reported, the capacity fading function of the average SoC of a cycle SoC_{avg}, the number of cycles nc of a certain cycle depth cd, and the idling time t of the battery at a certain SoC level are the relevant parameters used to define this study. The typology of the equation used is mainly suitable to evaluate the performance of battery cells for FCR application. As highlighted by the results exposed in Table 5.7, the yearly FCR online time is three times higher than the energy arbitrage one. Moreover, it is assumed that the SoC profile obtained from the year of investigation is kept the same for the ten-year roll-out time of the capacity fading estimation. As reference capacity fading, a 20% reduction is selected as in [16] which refers to the calendar EoL.

The short lifetime faced in Figure 5.4 could be addressed to the effect of the extra DSO operations. Indeed, the consistent extra number of activation reduces the idling time of the battery radically, as reported in section 5.3. Thus, the degradation of the battery's cells is further affected. Moreover, in the presented model, the upper and lower state of charge limits are not hard imposed limits due to the scope of the optimization tool to be assessed with several technologies. Hence, to ensure the stability and suitability of the battery system, it has been said that it is not needed to keep the hard SOC constraints in the design phase. However, as suggested in [70], the cycle depth strongly determines the capacity fading of the cells. The following section proposes a reduction in the range of SoC operation when Li-ion battery technology is considered.

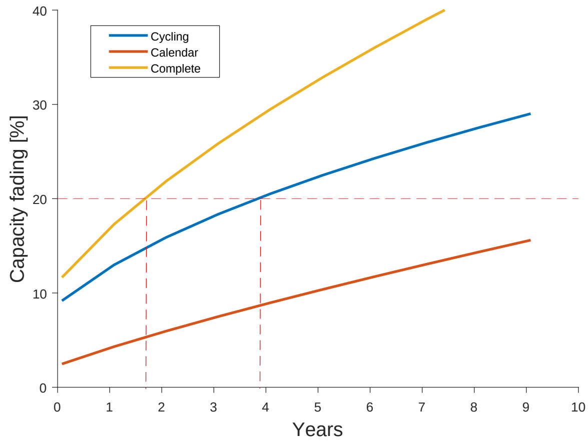


Figure 5.4: BESS lifetime projection. Complete degradation refers to the capacity fading due to cycling and due to aging (calendar). Capacity fading due to cycling occurs in 4 years with an overall lower than 2 years battery lifetime.

5.3.4. Proposed Solution

In this section, the results of the proposed solution are displayed. Additional SoC boundaries are added, limiting the spanning range of operation from 80% (DoC) to 20% (DoD). In Table 5.9 the results with and without DSO remuneration are compared. Thanks to the additional revenue stream, Case B remarks a moderate increase in the NPV, however, both payback time figures have risen above 3 years.

In terms of cell degradation, Figure 5.5 demonstrates that reducing the range of operation will considerably improve the lifetime, which has shifted to more than 5 years. The fading due to cycling and aging will occur at the BESS EoL. Thus, a trade-off between lifetime performance and financial return is essential to draw a complete picture of the business case.

Table 5.9: Financial analysis results of the proposed solution with SoC boundaries. Case A refers to when only market operation are considered, while Case B when also the DSO remuneration is taken into account

	Case A	**Case B**
Cycles year 1	160	160
Activation DAM year 1	405	405
FCR activ year 1	450	450
DSO extra activ	495	495
NPV	90k€	160k€
IRR	14 %	21 %
Payback	3.6 $year$	3.1 $year$

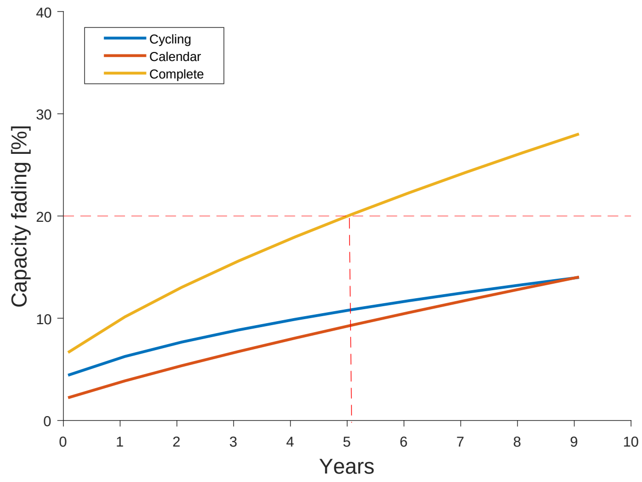


Figure 5.5: BESS lifetime projection with SoC limited to range 80%-20%. Complete degradation refers to the capacity fading due to cycling and due to aging (calendar).Overall improving in battery lifetime to more than 5 years.

Considerations

To sum up, operating BESS in distribution grids paired with a PV system and an EV charging station has reported economic and technical benefits for all the three players involved in the case study. The BESS owner would profit from a positive NPV and a low payback time which could be reduced under 3 years whether higher speculation is executed on the DSO remuneration agreement described in this thesis. Economically speaking, no assessment is outlined for the DSO. Its benefit relies on the technical aid that the BESS could provide by waiving the grid from peaks of power. It is known from the literature that fees have to be paid in case congestion occurs on the line, however, the lack of data did not make possible such evaluation. Finally, the PV-FC station owner would benefit from an overall 30% of grid connection tariff reduction. On the other hand, less energy coming from the solar plant could be sold in the spot market, and no possible feed-in tariff is examined. The technical downside of the case study concerns BESS cell degradation. Simulations have shown that application stacking leads to hard cycling of the battery, and therefore limiting the range of operation is essential. Bounding the DoD and DoC at 20 and 80 % respectively has improved the BESS capacity fading from 2 years to above 5 years, whereas due to the limited range of operation, the payback time has shifted once again to above 3 years.

5.3.5. Project Partner Case Study

This conclusive section of the chapter outlines an example using the commercial BESS from Alphen (TB-548-1C) of 521kWh/630kW. According to the data-sheet [71] the battery cells have an efficiency of 98,6% and the inverter efficiency is 97,0%. This leads to an overall η_{rpt} of 95%. The BESS is placed in the Fast Charging station environment with 500 kWp of PV and 250 kWp FC stalls. A peak shaving has been performed on the station performed equals 20% of solar production and 60% of charging intake. Since Alphen uses Li-ion cells, additional SoC boundaries are added, limiting the range of performance from 80% (DoC) to 20% (DoD). BESS $CAPEX$ and $OPEX$ are kept the same due to the confidentiality of the information.

The Table 5.10 below proves that using commercial battery in the Netherlands in the FC station environment has technical and economic potential for the BESS owner. Case B underlines a 30%

of IRR, which leads to a payback time of 2.5 years. Even in this case, the downside concerns cell degradation, which stays around 4 and 5 years. Furthermore, the cycling degradation curves prove that reducing the operational limit the wear due to cycling. Its representation is portrait in Figure 5.6.

Table 5.10: Financial analysis results using commercial Alphen BESS with SoC boundaries. Case A refers to when only market operation are considered, while Case B when also the DSO remuneration is taken into account

	Case A	**Case B**
Cycles year 1	245	245
Activation DAM year 1	475	475
FCR activ. year 1	450	450
DSO extra activ.	495	495
NPV	215 $k€$	295 $k€$
IRR	25 %	30 %
Payback	2.75 $year$	2.5 $year$

The Table 5.10 demonstrate that depending on the size of the BESS, the number of cycles and the online time differs quite significantly, with an increase of 60% in the number of cycles and 15% of DAM participation. On the contrary, DSO operation values do not differ because model's input parameter and executive priority.

Furthermore, such an additional case study confirms the model's adaptability to be executed regardless of the BESS size C-rate and other input parameters selected in the evaluation of the main case studies.

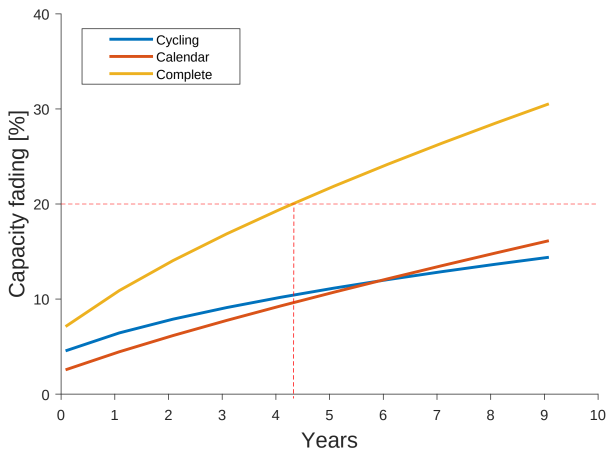


Figure 5.6: BESS lifetime projection using commercial Alphen BESS with SoC boundaries. Complete degradation refers to the capacity fading due to cycling and due to aging (calendar). Capacity fading due to cycling occurs after the BESS EoL. Overall lifetime between 4-5 years.

6 Conclusion

This final chapter concludes the thesis by firstly giving answers to the research questions. Secondly, a review and consideration of this thesis are outlined. Lastly, recommendations are provided on the suggested further research in the studied domain.

6.1. Answers to Research Questions

Using the results obtained in this work, the main research question *Are battery energy storage system (BESS) a possible profitable asset in the current energy transition phase? And what is the business case for BESS at distribution system level?* will be answered below. The aim of the model developed is to create a flexible tool to evaluate the economic feasibility of BESS operation in distribution networks (DNs). To accomplish this goal, several research objectives are elaborated as a guideline for the thesis. In the section 1.2.2 the four main research questions are outlined and defined with the intention to bridge the literature gap identified in the literature review. The answer to them is displayed in the following.

What are the set of functionalities to be performed by the BESS and the revenues streams at DS level?

From the literature, it is clear that BESS is a promising asset in future distribution grids, and in this thesis, it has been given proof. In the category of FTM use cases, several applications have been identified:

- Congestion relief: BESS can be used as an accumulator of energy to waive the network congestion and to relieve the overloading of the conductors due to unpredictable RES generation and stochastic peaks in load profiles
- Peak shaving: Another aid that BESS can bring in DN consists of flattening the generation and load profiles to decrease the maximum power at the grid connection point. Reducing the power exchanged to the grid, the owner of a power plant would benefit from the cost of the connection to the grid
- Ancillary service: BESS could be used for frequency control purposes and to improve the continuity of service of distribution grids. Furthermore, in case of fault storage system permit islanding operation of the distribution feeder, allowing a safe operation also during unintentional islanding.

- Energy arbitrage: BESS could variate their SoC also by selling and purchasing energy directly from the wholesale markets. Currently, in Europe, despite the standardized market product with easy access, business cases can be built out of energy arbitrage due to low spot market prices.

Many authors reported in chapter 2 have concluded that only energy products underestimate the revenues and the capabilities of the batteries. Nowadays, BESSs are still an expensive technology compared to other RES; therefore, combining ancillary services and other grid services will drive to capitalize higher revenues. In this way, stacking several remunerated revenues stream BESS's payback time would reduce and become more attractive for other stakeholders.

Currently, DSOs cannot hold a storage system that can influence the electricity market. Therefore a third-party owner has to be involved in order to provide the services mentioned above. Moreover, no clear framework has been developed yet to assess revenue streams for DSO service providers. This is also the case of the Netherlands, where transparent and robust tools have to be developed to assess financial incentives concretely.

How can be modeled the BESS market participation and DSO operations in an optimization problem?

Several studies have been conducted in the literature about the possible type of optimization problem. A MILP formulation has been investigated by authors that have applied BESS operating energy arbitrage and ancillary service market. Consequently, it has been adopted or the development of the model of this thesis. The model has been built to be as generic as possible by leaving several parameters as input of the simulation. In this way, different methodologies can be applied to define different specif cases in terms of countries, market requirements, and stakeholders. The BESS regulating equations communicate effectively with the other three modules, which define the DAM participation, FCR regulation, and the DSO operation blocks. The first two are shaped based on the ENSO requirements for limited energy sources, while the last module is composed of block parameters (power and SoC) which are case study dependent. In this work, a PV-FC station has been used to assess the BESS behavior when unpredictable power flows in the distribution feeder.

How much is a RES owner saving from the grid connection thanks to the storage system? Moreover, what are the DSO benefits and the BESS owner's total remuneration?

In DNs, BESS can be deployed for several purposes, such as enhancing the grid capacity in hosting renewable generators. The benefit that the BESS bears is twofold. The BESS could shave the power peaks on the RES owner side and reduce his contracted power with the grid operator. On the other hand, the DSO will benefit from relieving congestion from the grid, leading to economic penalties. The DSO could benefit from the lower power injected by the RES owner, but also it can call online the BESS when grid congestion is occurring. However, in the absence of data on congestion management at DS level, this aspect is not considered but will be left as future research.

As mentioned in this work, a PV-FC station has been used to assess the BESS business case. Several shavings of power have been performed in order to reduce the peak power flow. Nevertheless, it has considered the possible losses in remuneration of the BESS due to misalignment from the optimal operating point. The results are displayed in terms of the financial parameters NPV, IRR, and payback time. Due to the absence of a clear framework defining the remuneration for congestion relief service to the DSO, a possible scheme in terms of a bilateral agreement is proposed. Overall, the simulation concludes that stacking this service upon other revenue streams from market application increases the BESS capitalization, the NPV from 125k€ shifts up to 190k€, and the payback time reduces below three years. The extra remuneration coming from the agreement with the DSO will become a predominant factor in future markets where FCR application will not be as favorable as it is nowadays.

How can the lifetime of the battery system be evaluated?

Using a post-processing BESS lifetime model, this thesis does not include the lifetime in the objective functions. The simulation time is restricted by the 1-year dataset, which will be used as general reference input. The equations used have been developed to assess LFP BESS lifetime. From the results, the degradation of 20% of capacity occurs after two years. While, when more restrictive SoC boundaries are applied, limiting the range of operation to 20% DoD and 80% DoC shifts towards five years. Thus, it can be concluded that because of peak-shaving, the BESS online time increases by 25 % which drives to a significant cells' degradation.

6.2. Considerations

In this section, general reflections on the performance of the model are gathered.

The thesis has shown that combining various use-cases and services in the Netherlands leads to more profitable business cases for battery storage. Furthermore, it has proved that energy arbitrage opportunities entirely depend on the price spreads in the electricity prices and that proving a single service makes it very hard to overcome the high capital costs. FCR in the Netherlands can provide an additional source of remuneration. This market is assessed in this research and has expressed much potential to be beneficial for BESS. In particular, it has been shown that increasing participation in the FCR market directly led to higher profit margins. However, it strongly affects the degradation of the BESS [28]. Besides FCR, BESS has expressed potential in participating in other capacity markets due to their nature. They would always have the possibility of reserving capacity to be used. This has been demonstrated when the BESS was asked to provide additional power to meet the demand of the FC station, where the blocked power capacity of the BESS must always be available, even if it is not necessary due to the current method of providing the reserved capacity for the FCR market. In future capacity markets, the auction-based remuneration will be assessed for providing sufficient energy generation capacity for periods of peak demand [68]. Dutch neighboring countries such as the UK are already trading significant amounts of electricity. Although successful commercially competitive projects have emerged on capacity auctions, recently, it has been found out that by the end of 2022, the volume of installed batteries in the UK is set to outstrip the demand from frequency services, making a critical tipping point for PFR.

The result coming from the financial analysis shows that only after one year the facility becomes non-profitable despite the 'Perfect Forecast' scenario. Future research could look for extra revenue streams by providing other remunerated ancillary services (i.e., aFRR). Revenues from other ancillary services or other use cases could be very economically attractive if they can provide a secure revenue and lower the payback time to just one year.

When evaluating the possible extra revenues from the DSO many difficulties in the assessment have arisen since no precise remuneration regulation exists in many electricity systems (such as the Netherlands). Therefore, improved market mechanisms that offer long-term bilateral contracts could be designed to reduce the risks of an investment in BESS. This, however, still needs to be researched since much uncertainty still exists in determining the right level of financial incentive which is appropriate for BESS capable of offering such aid.

Regarding BESS capacity fading, literature has demonstrated that longer calendar lifetimes result in a lower number of cycles allowed per year, leading to lower annual profit margins. Therefore, short calendar lifetimes and high cycle lifetimes return the highest profit margins. On its turn, higher profit margins result in shorter payback periods. Nonetheless, it must be noted that shorter calendar life directly results in the battery pack needing to be more regularly replaced, which will significantly increase the $CAPEX$. Hence in future research, the trade-off between high annual profit margins with batteries with a short technical life versus a battery system with lower profit margins but longer lifetimes should be researched.

Concluding, the power production with RES is highly variable and unpredictable, leading to the need for optimization-based planning and operation. Energy systems optimization helps to reduce uncertainty or improve results in renewable energy systems. Although the deterministic optimization selected does not allow to have highly reliable results since using perfect foresight, the outcome results are overestimated. On the other hand, it reduces the computational time and the programming time compared to other stochastic models.

6.3. Future Prospects

In this final section of the thesis, the guidelines for future research are shown.

Additional markets to explore

This research defined that the DAM and FCR markets were the most accessible markets for BESS based on technical requirements, time scale, and data transparency. However, in an optimized trading strategy, the most significant opportunities for BESS application lay in the fast response market, such as primary and secondary frequency regulations, named FCR and aFRR, respectively. With more data availability and time to build an additional module, the aFRR market could have been shaped since it represents an added value for the BESSs business case.

Furthermore, in section 2.4 is mentioned that electricity prices in the intraday are highly volatile and unpredictable, in addition, the continuous trading structure allows BESS to change their position up to 5 min before the GTC. The intraday market can represent an extra revenue stream and may be used to perform SoC management to adjust the position to be commissioned in frequency markets, where higher revenues are caught. This market has not been modeled due to the lack of transparency and time to obtain a reliable dataset. A complete business case could be shaped by stacking the already modeled FCR and DAM, those two short-term trading markets.

A compelling future strategy could be to bid regularly on aFRR down-regulation, as it yields considerable revenue and does not require high cycling. On the long-term market's side, the strike price approach could be maintained to select which bids to place and knowing in advance the necessary energy to be provided in those blocks. Finally, use the short-term markets to balance the SoC to meet the requirements for participating in the frequency market. For example, a couple of hours before participating in a previously awarded FCR delivery, the battery could purchase energy from the Intraday market to reach the required SoC. This function would result in a "smart SoC management" strategy. When the BESS is fully charged, it could use the same approach and discharge in the Intraday or DAM to always maintain a value close to the requirement from the long-term awarded market auction and not incur in penalty.

Internalize the capacity fading equations

In this work, battery cell degradation is performed after the optimization algorithm has computed the results for the yearly simulation. Currently, cycling limitation is imposed by additional ramping cost; however, internalizing in the objecting function those equations would improve the reliability of model performance. On the other hand, this will increase the computational time and the formulation of the optimization problem due to their nonlinear configuration. This internalization could include a decision threshold that considers the minimal revenues that have to be generated in one cycle. These revenues should be able to cover the marginal costs of the system. These costs should include $OPEX$ but also the costs of capacity degradation.

Selection of specific technology and sizes

Given the flexibility of the model, many more cases can be investigated. For instance, already changing the SoC margins, different outcomes have been displayed. It would be interesting to study the proper BESS size for a given system at DS level. A Monte Carlo simulation could be used in successive researches to simulate the effects of varying energy and capacity of the BESS and select the most favorable outcome.

Improve forecasting methods

In the thesis, a price-driven hybrid forecasting method has been proposed. Its accuracy was out of the scope of the work, however, additional studies and methodologies could be applied to obtain a reliable forecasting dataset. In order to do so, deep neural network architectures could be studied. The next hour's electricity price prediction may be investigated using past electricity price values and features related to energy generation and weather conditions. In the future, the effectiveness of simulating the case for BESS will significantly increase due to decreasing capital costs of battery systems and the increasing price volatility. The main challenge to significantly increase the revenues will be accurately forecasting electricity prices.

Assessment of DSO remuneration

A proposed assessment is proposed in this thesis in section 5.3.1 of chapter 5. However, it falls out to future work to understand and properly evaluate a possible remunerated framework for DSO services.

In conclusion, with this research, a contribution is delivered towards realizing a business case of BESS operations in distribution networks. Insights are provided on the economic return that battery technology can provide when performing energy arbitrage, primary frequency regulation, and additional DSO operation. However, figures could variate country by country; therefore, before selecting which application to tackle, a detailed analysis of the dataset is strongly advised.

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