Batteries and energy arbitrage

A techno-economic analysis of electricity arbitrage opportunities for utility-scale battery energy storage in the Netherlands

Master Thesis by

D.E. Hugenholtz

Written by

Dorine Elisabeth Hugenholtz

Under supervision of
Dr.ir. F. Bliek
Dr.ir. F.M. Mulder
Dr.ir. R. Hakvoort
Dr.ir. L.J. de Vries

September 2019 - August 2020

Student number: 4317270

Cover image from www.pexels.com.

Acknowledgments

This thesis could not be written without the extensive help of Lennard Sijtsma and Frits Bliek. They were both always ready and available to give me any advice. Furthermore, Fokko Mulder, Rudi Hakvoort and Laurens de Vries have offered their help where needed. With this, I would like to express my gratitude to all of them.

Despite the challenging times caused by the Coronavirus, I am happy to be able to finish this report and finalise the master Sustainable Energy Technology at the Delft University of Technology.

Dorine Hugenholtz

Abstract

As the variable renewable energy share keep on increasing throughout the energy transition, power systems require more and different flexibility measures. Battery energy storage can provide these essential services that enable the energy system to decarbonize and transform on short time scales. Energy arbitrage, the trading of electricity on the electricity markets, can create economic value for batteries.

This research assesses the energy arbitrage opportunities for utility-scale battery energy storage in the Netherlands. It compares five different battery technologies and defines the optimal size and power capacity with a linear mixed-integer Matlab optimization model. Furthermore, the operation of for the most optimal technology is simulated for one year with a Model Predictive Control algorithm to be able to compare the effects of forecasting accuracy of the electricity prices on the estimated profits.

The results show that according to optimized planning and dispatch in the operation of a battery system can lead to financial opportunities in the Netherlands regarding energy arbitrage for flow batteries. If not today, then in the future. It has been shown that towards 2030 the business case for battery energy storage will significantly increase due to decreasing capital costs and increasing price volatility with the rise of the VRES and phase-out of fossil energy sources.

With this research, a contribution is delivered towards the realisation of commercially operating an independent utility-scale battery energy storage facility. Insights are provided on what battery configuration is best suited for energy arbitrage purposes and the effectiveness of simulating the optimized operation of a battery facility with a model predictive control method has been shown. This has lead to clearer insights into the profitability of operating a BESF in the Netherlands.

Contents

List of Figures

List of Tables

List of Acronyms

aFRR	automatic frequency regulation reserve
BESF	battery energy storage facility
CAES	compressed-air energy storage
CAPEX	capital expenditures
DAM	day ahead market
DOD	depth of discharge
ESF	electricity storage facility
FCR	frequency containment reserve
FRR	frequency regulation reserve
GW	gigawatt
GWh	gigawatt hour
IRENA	International Renewable Energy Agency
kWh	kilowatt hour
LCOE	levelised cost of electricity
LCOS	levelised cost of storage
LP	linear programming
mFRR	manual frequency regulation reserve
min	minutes
MPC	model predictive control
ms	milliseconds
MW	megawatt
MWh	megawatt hour
NaS	sodium sulphur
Ni-Cd	nickel cadmium
NMC	nickel manganese cobalt oxide
OPEX	operational expenditures
PHS	pumped hydro storage
PV	photovoltaic
RE	renewable energy
RES	renewable energy sources
s	seconds
SOC	state of charge
TSO	transmission system operator
TWh	terawatt hour

VRES	variable renewable energy sources
VRFB	vanadium redox flow battery
WACC	weighted average cost of capital

1 | Introduction

Since the late 19^{th} century, scientists have been showing that the climate on earth is changing due to human activity. Furthermore, in the 1960s, a clear correlation was found between carbon dioxide emissions and its warming effect on earth's temperature [1]. Since then, the tremendous impact of the increasing earth temperature has become clear. However, public awareness has only recently begun to increase. Activists stood up, governments from the whole world joined their forces in the Paris Agreement, and the number of scientists focusing on sustainability and renewable solutions has grown exponentially [2]. Even schoolkids have shown their concerns about the rising temperature on earth and its consequences [3]. The urgency of action against climate change has become a returning topic in every-day life.

This 'energy transition' that will need to occur to prevent the climate from changing includes the switch from fossil to renewable and often decentralised energy sources. This transition causes the need for changes across different players within the energy sector. Examples are the generation, transportation and demand sides of the system. To further break down; the demand sector, for example, consists of industry, agriculture, residential and commercial electricity usage. All these different aspects and roles make the energy system very complicated. Therefore, the energy transition is happening very slowly [4]. Nevertheless, researchers have not been held back to try to tackle the many challenges.

In line with the developments, the Dutch government has recently accepted a national climate agreement. Among others, this states that renewable energy sources (RES) will provide 70% of the electricity supply of the Netherlands by 2030. The aim is to generate 49 TWh of offshore wind power and 35 TWh of solar and onshore wind power annually. These measures will help to build a sustainable society and will significantly reduce the carbon emissions of the country [5]. Nonetheless, the installation of such significant numbers of renewable energy facilities does not come without its balancing challenges and their accompanying costs, especially when one also considers the forecast increasing levels of electrification in industry [6]. One of the possible solutions to cope with these challenges is energy storage. Energy storage could store excess electricity from the grid when there is more generation than consumption and vice versa when there is an electricity shortage. This process is called energy arbitrage and has many potential benefits [7]. Next to financial opportunities, this results in more possible benefits of energy storage, which are [8]:

1. Providing solutions for the increasing ramping rate capacity requirements that come with increasing integration of RES
2. Reducing costs or defer investments on generation, transmission and distribution levels

3. Reconnecting supply and demand

Summarizing, batteries are likely to become a necessary part of the future power grid. Therefore, this research focuses on a specific size and type of energy storage; utility-scale batteries. The costs of these storage systems can be high, but the value of the described benefits have the potential to be much higher [9, 10]. Nonetheless, the economic viability is often up for debate [11]. Moreover, the exact configuration of such a utility-scale battery system for energy arbitrage and application on the Dutch power market have not been identified. This research will, therefore, focus on finding optimized conditions and strategies to implement an independent large scale battery energy storage facility (BESF) for energy arbitrage purposes in the Netherlands.

First, the currently existing battery technologies will be identified. Secondly, the Dutch electricity system will be analyzed to identify possible revenue streams and strategic market participation opportunities. Lastly, an operational tool called MPC will be used to optimize the charging and trading schedule for the battery system.

Based on optimization and simulation algorithms the maximum reachable profits and the economic viability are defined for the various battery technologies and sizes. Moreover, the simulation part is done with a relatively new algorithm called model predictive control (MPC). The MPC simulation can be used to simulate an optimized trading strategy for the battery system with a limited forecast horizon. The MPC is a more realistic method compared to simpler models assuming perfect foresight.

1.1 Research question

The above described leads to the following research question:

'What are the technological and economic opportunities of energy arbitrage for large scale battery energy storage in the Netherlands?'

This question will be answered by finding answers to the sub-questions mentioned below.

1. What are the ideal technological characteristics for a BESF in regard to energy arbitrage?
    (a) What characteristics are most important?
    (b) What battery technology is currently the most beneficial?
2. How could a BESF trade electricity on the different electricity markets in the Netherlands?
3. What are the maximum profits reachable for an BESF with energy arbitrage?

1.2 Structure of the report

This report starts with Chapter 2 which contains background information on the topic and a review of the existing literature. To be more precise, information regarding the Dutch power system and its markets, as well as an explanation of the various existing storage technologies is provided, and an introduction to MPC is given. Next, the twofold methodology of research is described in Chapter 3.

Followed by the results of the research in Chapter 4. Then, Chapter 5 and 6 present the discussion and concluding remarks, respectively. These chapters will also include an answer to the research questions and recommendations for further research.

2 | Background

This chapter will describe all relevant background information and will show what already has been researched regarding battery energy storage in the Netherlands. It starts with discussing the energy transition in the Netherlands. Then a description of the Dutch power system and its electricity markets is given. Followed by a description of various battery technologies, their costs and up- and downsides. Lastly, an introduction to MPC is given.

2.1 Energy transition in the Netherlands

To tackle climate change and to accelerate the energy transition, the Dutch government has set a target of 14% of the total energy consumption to come from RES by 2020. By 2030, this is targeted to be minimal 27% and in 2050 100% [5]. In 2018, the consumption of renewable energy was only 7.4% of the total, see Figure 2.1. To be more precise, the share of biomass energy was 4.51%, wind energy 1.7%, solar energy 0.6% and the remaining by other small RES [12]. The total end-use of renewable energy has been growing, with an average of almost 6% per year since 2010. To reach the targets of the Dutch government, the total share renewable energy of the consumption in the Netherlands has to be doubled within two years. Now 2020 has started, time is limited to reach the goals [13]. This fast increase of intermittent energy sources in the Dutch electricity mix helps to decarbonize the energy system and potentially avoid climate change.

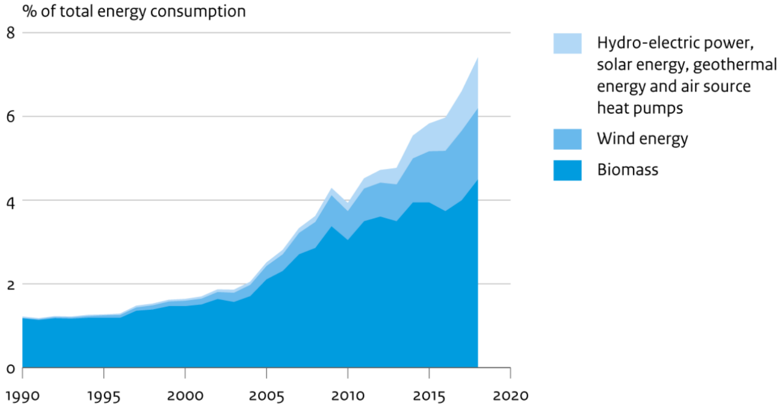


Figure 2.1: Renewable energy consumption by source in the Netherlands in 1990-2018 [14].

Moreover, in 2018, 18.1 billion kWh of renewable electricity has been produced in the Netherlands, which is about 15% of the total electricity usage, see Figure 2.2. Around half of this renewable electricity is generated with wind turbines, which have a total installed capacity of 4.4 GW. The installed capacity of solar panels in 2018 was about the same size [13, 15]. In 2020, the total installed capacity of PV already passed 6 GW [16]. For wind energy, it is estimated that the installed capacity reaches 6 GW soon.

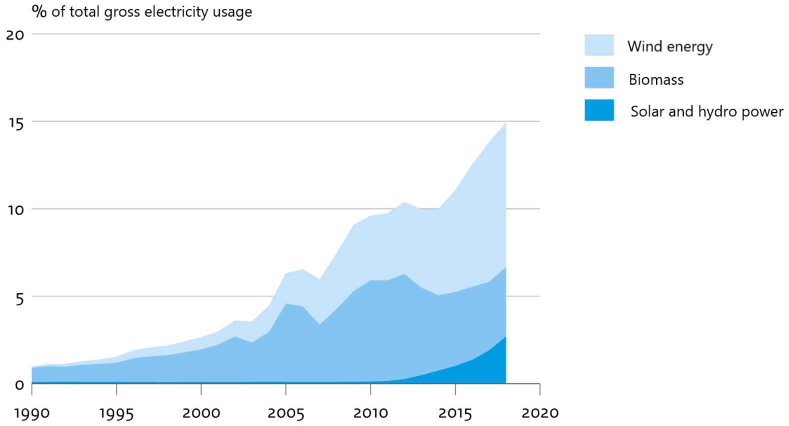


Figure 2.2: Production of renewable electricity in the Netherlands in 1990-2018 [13] (translated).

2.1.1 Challenges of the energy transition

The intentions to tackle climate change are there. However, in practice realising the plans appears to be difficult. Drastic reductions in fossil energy usage have not occurred yet. Various obstacles hinder the Dutch energy transition. Furthermore, the significant increase of variable renewable energy sources (VRES) does not come without challenges. For example, well-known difficulties of the implementation of RES in the energy mix are the supply and demand mismatch, grid instabilities and the substantial land-use requirements [17]. Also, grid reinforcements and back-up capacity might be costly, but necessary expenses to enable the growing share of renewable energy (RE) [18]. The fossil alternatives for electricity generation are often still the cheapest option [19]. Regarding the specific case of the Netherlands, another limitation for the energy transition is its geographic situation. Lack of elevated or mountainous areas and the high population density significantly reduce the number of available options.

The most important of these challenges for increasing the RES share in the electricity mix, might be the balance between supply and demand. The unpredictability and intermittent nature of solar and wind energy resources do not always match with relatively inflexible demand profiles. This unpredictability also causes grid instability regarding voltage and frequency levels will require more controlling efforts [17]. Significant investments are necessary to reinforce the grid and install large amounts of backup capacity and storage capacity [18]. The risks that come with these required investments of this scale are very high, and up to today, investors have not been very interested.

Moreover, this lack of economic incentive to switch to the RES on the electricity generation side has many reasons. Continuously changing laws and regulation in the energy markets cause a significant investment risk and fossil fuels are still often cheaper than the sustainable ones [19]. Furthermore, the Dutch economy is still very depending on fossil energy, which hinders the phase-out of these non-sustainable energy sources. Therefore it is needed to build a consistent and long-term transition strategy for the country [20]. The first steps for this strategy have already been undertaken. A recent action of the government is the set up of incentives to accelerate the energy transition. Money from taxes on electricity and natural gas usage is used to subsidise RE projects [21]. Furthermore, the extraction of natural gas is being reduced and will be fully phased out by 2030. Also, a plan to stop the usage of coal-fired power plants by 2029 has been agreed upon [22]. These measures will give room for the RES to increase their share in the national electricity generation.

2.2 Dutch power system

The Dutch power system, which is fully liberalized, can be roughly divided into four physical assets: the generation side, the transmission network, the distribution networks and the load or consumption side.

The generation side determines all electricity generating units. From coal power plants to offshore wind farms, many different electricity generation techniques exist. Often groups of generating units are bundled to form the portfolio of a balance-responsible party. In the Netherlands, there is only one transmission system operator (TSO), which is TenneT. The distribution of electricity between the high voltage grid of TenneT and the consumers is represented by several companies. In general, every region has a separate distribution company that is responsible for the low voltage grid and the connectivity with the electricity consumers. The load of the power system is the electricity usage of the Dutch households and industries. A simplified overview of how this works is shown in Figure 2.3. The generation and consumption sides are indicated with the transmission network in between. The battery energy storage facility researched in this report is connected to this transmission network, acting as an electricity generator and as a large consumer simultaneously. This position in the power system is relatively new. So, the whole Dutch operation and regulation system is not designed for storage parties. That could offer challenges but might also have the benefits of being a pioneer.

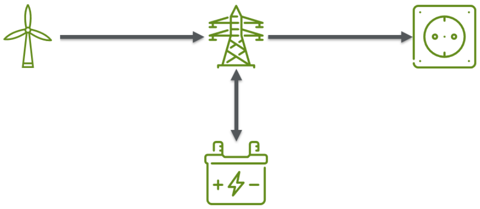


Figure 2.3: Simplified topology of the power system with an ESF connected to it [23].

2.2.1 Power system flexibility

Next to attracting investments, another big challenge is the already mentioned increasing need for power system flexibility. A power system always requires a certain level of flexibility to overcome unexpected mismatches between supply and demand. However, when the intermittent RES are further penetrating a power system, this flexibility need will increase [11, 10]. Moreover, the uncertainties raised by the decentralised and two-directional future of the power grid ask for a systemic change of the electricity sector. If too many or too big imbalances occur, electrical appliances could be damaged, and blackouts might occur. In the Netherlands, the increasing balancing market volumes (the intra-day trading volumes increased with almost 50% from 2017 to 2018) could be an identifier for increasing flexibility needs [11, 24]. Many different options exist to enable more flexibility for the grid, on short but also on longer time scales. Overall, it can be said that increasing wind and solar energy shares in the electricity mix increase the need for flexibility. Among many options, energy storage is very likely to play prominent roles in providing flexibility to future energy systems. Furthermore, innovations could enable demand response strategies, which will create more flexible load profiles. Electric vehicles and dynamic electricity pricing also have a significant potential to contribute to more elastic demand and hence allow for better balancing of supply and demand [25, 18, 11]. A general overview of the various options to create more flexibility and resiliency in a power system are shown in Figure 2.4.

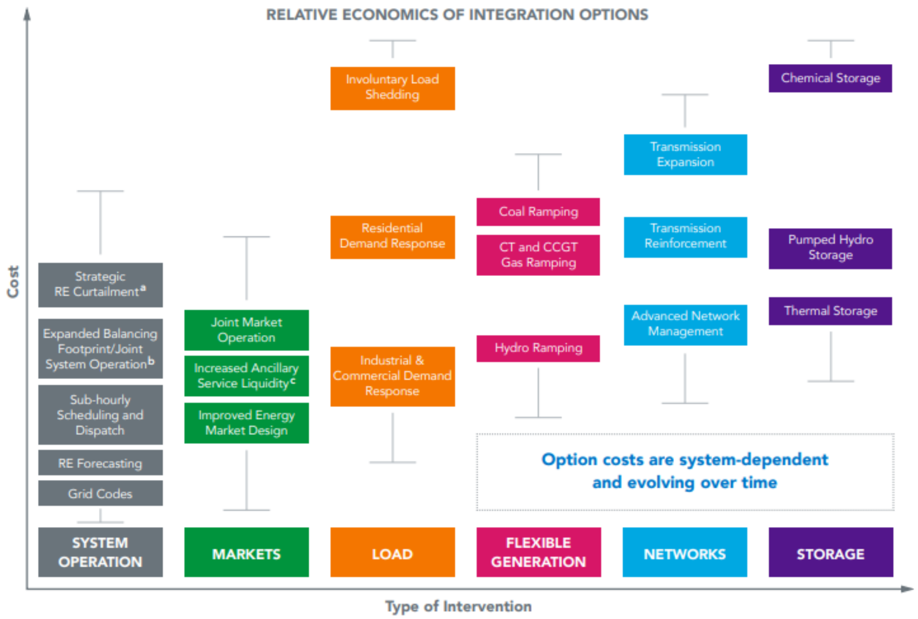


Figure 2.4: Flexibility options for the power grid and their relative costs [26].

Specifically, in the Netherlands, more flexibility can be created by specific investments in the generation, consumption, storage and transmission parts of the electricity system. Furthermore, regulatory adjustments and new market designs are also examples of measures that could lead to increased flexibility. The organisational and market structure are essential in creating the desired operation of the electricity system [11].

Regarding improvements in the electricity grid, it can be said that the interconnection capacity of the Dutch transmission lines with neighbouring countries is already quite big. There are connections with Germany, the United Kingdom, Belgium, Norway and Denmark. Even though this interconnection capacity is estimated to grow even further, it is very likely that it will not be significant enough if the VRES-shares keep on increasing. However, the current interconnections shift the need for more flexibility in the Netherlands up to 2023 or even 2030. If the energy transition would happen faster, extra flexibility measures might be necessary.

If more flexibility is required in the future, the development of storage capacity will be crucial for the Dutch power grid. Well developed battery technologies or new technologies like compressed-air energy storage (CAES) are plausible solutions for more flexibility [18, 11]. Moreover, storage solutions are forecast to play a significant role in providing flexibility and hence enabling the energy transition. It will reduce transmission constraints and defer grid upgrades. On the demand side, it can help to reduce and shift peak demand [10].

2.3 Dutch power markets

The Dutch power market is fully liberalised, and any independent party can participate in the electricity trade. However, the markets are carefully designed and monitored by the government to make sure all end-consumers always have access to electricity for an affordable price. The market design includes several requirements and obligations to be acknowledged as a participating party on the different market segments.

The various segments of the wholesale electricity market are designed to maintain the balance of the system at any moment in time [27]. The Dutch wholesale power market can be divided into three categories: the bilateral market, the spot market and the balancing market. In Figure 2.5 a general overview is given of the time frame and various wholesale markets.

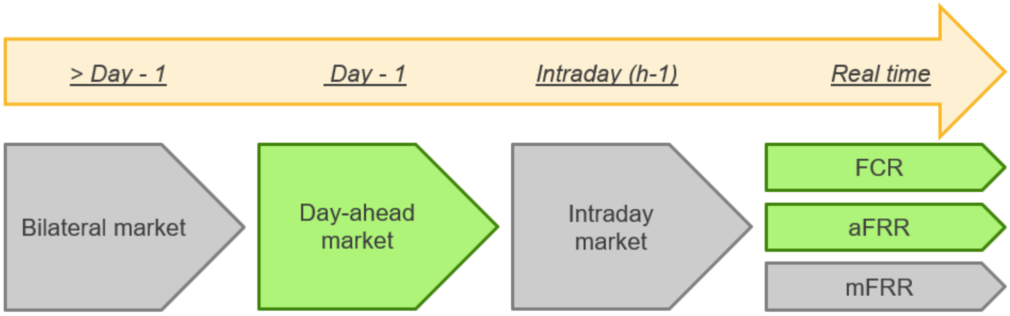


Figure 2.5: Time schedule of the Dutch electricity markets. In green the markets assessed in this research.

Energy storage has the potential to result in a lower levelised cost of electricity (LCOE) by adding value to the generated electricity in several different markets. It depends on various factors if a specific electricity market is relevant for a BESF. It can depend on the availability of the market results, the technical energy and power requirements of each market and the time scale of the market concerning bidding plays a role. Lastly, a market is only interesting for energy arbitrage purposes if there is a significant price incentive to be able to generate revenues by electricity trade.

The following subsections will give a more in-depth overview of the various electricity markets and their characteristics. Also their in- or exclusion in this research will be explained based on the above-mentioned criteria for accessibility.

2.3.1 Bilateral market

The bilateral market is the forward or futures markets. The majority of all electricity trade happens in this market. Trading occurs several years ahead up to approximately just one week ahead. The market is very little volatile and mainly covers electricity baseload. Prices are based on long term strategies and decisions. They could, for example, be influenced by oil prices, political changes, import and export regulations of fossil resources or emissions rights. Closer to the date of execution the prices can also be influenced by weather forecasts for example [11]. Furthermore, the bilateral agreements are not publicly disclosed and therefore market results are not available for other parties. Therefore, this market is not included in this research.

Moreover, this research focuses on short term battery electricity storage facility for arbitrage purposes. Since the bilateral market consists of fixed long-term contracts, often for multiple years, it is out of the scope of this research. Regarding seasonal storage, the bilateral market has the potential to be interesting for arbitrage with energy storage facilities. However, batteries are not the most suitable technology for electricity storage over multiple months.

2.3.2 Spot markets

The spot market in the Netherlands is divided into two sections. First, the DAM and second the intraday market [27].

Day-ahead market

The spot market in the Netherlands is called the day ahead market (DAM). The market is an internationally operated electricity auction for the next day. At noon every day, the auction is closed, and the dispatch is determined for each hour of the next day. Around 20% of all Dutch electricity trade happens on the DAM. Since this trade is closer to the moment of execution, the market participants can better forecast the electricity needs of the country, compared to the bilateral contracts. Electricity supplies can offer bids on an hourly basis. The purpose of the market is to overcome any forecast mismatches that result after the electricity traded on the bilateral market is implemented. Bidding happens anonymously for the supply of power from the generators or consumption from large consumers or retail companies. After the closing time of the auction, the market operator, EPEX Netherlands, clears the market by determining the electricity volumes and the clearing price [11].

Since the market results are available, technical requirements of the market can be met with battery technologies, timescales are suitable for batteries and there is a price incentive, this market will be assessed in this research.

Intraday market

After the DAM it is very likely that there is still a mismatch between actual demand and supply. Closer to real-time, extra electricity can also be traded on the intraday market. Hence, predictions are even more accurate than on the DAM. The intraday market is based on a similar principle to the DAM. However, it is issued on the day of execution itself, up to an hour in advance. Typically, the price spread is of the intraday market prices is bigger than for the DAM. Wider price spreads are favourable for electricity arbitrage purposes. Nonetheless, the volumes traded on this market are very small in the Netherlands compared to the DAM and only used to make adjustments to previous trades [11]. It is likely that when more VRES are penetrating the electricity market, the intraday market becomes more important. However, the DAM is forecast to change, limiting the importance of the intraday market, see Section 2.3.5. Furthermore, the availability of market results information is very limited compared to the DAM. Therefore this market is not further assessed in this research.

2.3.3 Imbalance market

After all of the capabilities of the markets mentioned above, mismatches between supply and demand on the actual moment of dispatch still occur. The reason for this is that it is relatively impossible to forecast electricity demand and supply with a 100% accuracy. Mismatches could be caused by the unpredictable behaviour of consumers, weather forecast errors, and for example, mechanical failures. Therefore, most of the time, there is a certain level of imbalance in the system. TenneT, the TSO, is responsible for maintaining the balance in the system at the right frequency [11]. To avoid that the voltage drops or blackouts occur three imbalance mechanisms have been created. These mechanisms are also called 'ancillary services'. The three levels of imbalance market structures in the Netherlands were previously called primary, secondary and tertiary imbalance reserves but today they are called frequency containment reserve (FCR), automatic frequency regulation reserve (aFRR) and manual frequency regulation reserve (mFRR), respectively. A distinction is made between balancing energy and balancing capacity. A part of these balancing mechanisms are contracted by electricity suppliers or consumers upfront, and others can be realised by placing upward or downward bids for balancing power. Other ancillary services are black start capacity and reactive power supply to maintain the voltage level [27]. For the balancing mechanisms, energy storage could be commercially attractive on the frequency containment reserve (FCR) and the frequency regulation reserve (FRR) (automatic and manual) markets [28].

Although the market results of imbalance markets are published after the delivery time slot, the markets still have the potential for the BESF [28].

Frequency Containment Reserve

The FCR is a reserve capacity that can be automatically activated after a few seconds of imbalance in the system. Market participants can make a bid by offering a certain amount of power capacity. If accepted and activated, the contracted power must be up and running within 30 seconds [29].

Furthermore, the capacity has to be available for at least 15 minutes, and the generating party has then two hours to restore its electricity supply [30]. For 2019, TenneT had to contract 111 MW in total by rules of the European electricity market. At least one-third of this had to be contracted within the Netherlands [31]. Furthermore, it has been shown that the Dutch primary control market, offer significant financial opportunities for battery energy storage facilities [32].

Frequency Restoration Reserve

The aFRR, or secondary reserve, obliges the electricity supplier to have the contracted volume within 5 minutes if activated. Every 4 seconds, a new measuring impulse is sent to the regulator for optimal balancing control [29, 31].

If there is still a mismatch after the two previously mentioned imbalance mechanisms, the mFRR can be activated. This reserve power is mainly used for more extended periods of frequency imbalance of the grid. Within 15 minutes, the contracted power volume must be running if activated. The volumes can be bid by any market participant that fulfils the qualification. The contracted volumes can support the grid for several minutes up to a few hours [29]. The mFRR market generally requires quite large amounts of electricity, while being relatively nontransparent and does not offer significant price incentives [28]. Therefore, the automatic aFRR market will be researched, as this is the most transparent and easiest to forecast market of the two FRR markets [33]. Moreover, the aFRR market offers large price spreads, which is favourable for generating revenues from trading electricity.

Summarizing, from the six different electricity markets in the Netherlands only three (DAM, FCR and aFRR) are identified as interesting for a large scale battery energy facility with energy arbitrage purpose.

2.3.4 Market entry barriers

In the Netherlands, typical entry barriers for energy storage facilities to participate in the electricity markets. They are categorized as regulatory barriers and market barriers. The main ones are the following [27]:

1. Regulatory barriers
   - Absence or inadequacy of legal classification: The role of being a buyer and seller of electricity at the same time is new in the system. So, the Dutch law and regulation system is not built for parties like the ESF. This could offer challenges, however, it might also have the benefits of being a pioneer and setting the standards. Currently, storage facilities are both generators and consumers. No legal definition exists for being both in one. This leads to double taxes. A tax must be paid for consuming electricity when the facility is charged and then when end-consumers use the electricity which is discharged from the facility a second consumption tax is paid over the same electricity. This makes the electricity very expensive and reduces the profitability of a BESF.
   - Too little (financial) incentives for time-shifting of electricity supply and demand: Storage entities are not registered as renewable energy. Therefore, they fall out of scope for any RE incentive.

   - The unbundled electricity system led to the prohibition of owning storage facilities for TSO's: Commercial activity of purchasing and selling electricity is not allowed for regulating companies.
   - No regulatory framework exists that states how service provides, like storage facilities, could benefit from providing their services to the grid. For example, the deferral of grid investments with storage capacity has great value for the TSO. However, it is not clear how or who would pay for the storage.

2. Market barriers
   - Minimal capacities on the balancing markets: Those markets require minimum bids of 1 or more MW, but lots of battery installations are smaller than that.
   - Availability for especially the FCR market is a barrier of BESF: That market requires the facility to keep a certain amount of power capacity available the whole time, with the risk that it is not called. This uncertainty prevents the facility from the opportunity to use the reserved capacity in the other markets. This technical restriction prevents that capacity is sold twice.
   - Energy arbitrage builds upon the price differences of the markets: Even though arbitrage is a proper incentive to develop battery storage facilities, it could happen that if battery participation in the markets become significant, the price spreads will naturally flatten out, reducing profitability. However, based on basic and natural market mechanisms, it can be said that market participation will stop increasing if profitability is not ensured due to the lower price spikes.

Moreover, as earlier described, transmission improvements are a threat for energy storage facilities. Especially, since the deferral of those investments is not provided with any remuneration. A resilient and high capacity transmission grid can be seen as a direct substitution option for energy storage because both reduce operating costs by avoiding local supply and demand mismatches [34]. The larger, gird wide average mismatches or peaks, for example on a seasonal level, remain present, however. Nonetheless, a grid reinforcement could lead to smaller business cases for energy storage [35]. However, the significance of the thread depends on the time horizon one is looking at. On smaller time scales, up to a few years, grid reinforcements are less threatening for the battery business case. Especially when solely looking at energy arbitrage. In the Netherlands, it seems that those investments in the grid are generally cheaper than storage solution in the long term. Nonetheless, with the decreasing technology prices and slowly increasing need for flexibility, storage can be more profitable on short terms and potentially also on the long term [11].

To overcome the market barriers, general enablers for an increasing electricity storage market are [36, 8]:

1. The cost and performance improvements of various technologies
2. Modernization of the grid and its operational structure
3. The global energy transition towards RE
4. Financial incentives and national policies, like long-term contracts that secure revenue streams

5. Fossil-fueled electricity generator phase-outs
6. Increased transparency and accessibility of the power markets
7. Spreading knowledge and carrying out of pilot projects

Also, increased penetration of RES in the electricity mix results in higher profitability of a storage facility. The increasing RE capacity could more often lead to electricity excesses or scarcities. However, when the share of RES becomes very high, there is a risk that the price spread in the spot market reduces, which reduces profitability. That can be explained by energy discharge moments becoming more scarce because over- or undersupply of electricity moments will happen less frequently. That creates a need for more extended periods of storage capacity and reduces the need for high cycle efficiencies [35, 34]. Summarizing, it can be said that electricity storage solutions can provide multiple services to the electricity network and many benefits for electricity users and generators [10]. In more detail, analysis of the Dutch electricity market showed that there is potential for positive business cases for battery energy storage [37].

2.3.5 Forecast changes in the system

Electricity markets in the Netherlands have historically always been evolving with a relatively fast pace. Therefore, the above-described market structures will also be subject to changes in the coming decades. As earlier mentioned, the energy transition pushes the Dutch electricity system towards its boundaries. Possible changes in the regulatory measures of the system that could create a more beneficial environment for energy storage could be the avoidance of double grid connection fees or electricity taxes for ESFs and market design changes.

Further possible changes that are likely to happen are for the DAM to change to smaller time slots — for example, going from the current hourly auction to an auction for every quarter-hour. Also, it is expected that the auction will change its closing time. It is likely to change from closing at noon the day before, to closer to real-time. These changes possibly reduce forecasting errors and hence to reduce the imbalance.

The FCR market has been subject to a couple of changes in the past years. As of the 1st of July 2019, the weekly auction period is changed to a daily auction. Currently, the auction closes at 3 P.M. every day for bids for the next day. That is also the schedule used in this research. However, as of the 1st of July 2020, the market changed from a daily to an auction period of 4 hours [30]. These changes are implemented to create more flexibility within the primary control of the power system.

Lots of discussions have been going on in the Netherlands and its neighbouring countries to switch to a capacity market, based on capacity payments (€/MW), instead of an energy-only market, based on energy-based payments (€/MWh). France and the United Kingdom have already made this change. The need for capacity markets in the Netherlands is not yet very high, and there are no plans to switch from the energy-only market to a capacity market. However, in the farther future, it might become unavoidable if the VRES are gaining a larger share in the electricity mix [18]. Capacity markets enable more flexibility, but it could also cause over-stimulation of the conventional power plants, reducing the RES usage. Moreover, it could reduce the development incentive for new flexibility options that would have more potential on an energy-only market [11].

Lastly, it has been advised to trade electricity closer to real-time, to reduce the impact of forecast errors of variable renewable energy sources. That could not only lead to better integration of markets with different time horizons but also better combination of congestion management with market clearing. Trading would become a matter of operational decision making, rather than strategic [38, 11].

2.4 Energy storage technologies

As briefly touched upon in the introduction, energy storage can provide many different advantages for the energy system. Some of the most important values of storage are that it can prevent network congestion and contingency, reduce grid management costs, shift peak demands, avoid curtailing RES and over-sizing systems and, lastly, it can add reliability services to overcome voltage drops. Generally, energy storage is seen as an inherent solution in future energy systems with high levels of VRES and smart grids [39].

Electricity can be stored in many different forms and has many different use cases in which it can provide solutions for the energy transition. Historically, the most widely used form of electricity storage is pumped hydro storage (PHS). It has been used to shift electricity demand peaks and reduce generation costs. Nowadays, other technologies like battery, thermal and mechanical storage technologies are implemented more and more often. However, their economic viability is more challenging [26]. Although being generally one of the more expensive options to create more flexibility in the power grid, a lot of research has already shown that battery electricity storage could be profitable and prices for the technologies have been dropping very fast. Also on the larger utility-scale competitive projects have emerged [7, 9, 10]. Nonetheless, the historically relatively high prices of the battery technologies, lack of standardization and insufficient policy and market design made it very hard for utility-scale battery facilities to emerge on the market [36, 37, 40]. To accelerate this and overcome the above-mentioned hurdles, this research focuses on utility-scale energy storage.

Globally, it has been estimated that the overall energy storage capacities of 2017 (4.7 TWh) will triple up to 2030 in a scenario in which countries double their VRES shares. Specifically, for not-PHS the capacities are forecast to increase from 162 GWh in 2017 to 5.8-8.4 TWh in 2030. The (stationary) battery capacity will at least multiply by a factor 17 up to 2030 in the double RE scenario. On utility-scale IRENA estimates that in this same scenario the installed capacity will grow from 10 GWh in 2017 to 81-187 GWh in 2030 globally [10].

As mentioned before, there are a lot of different technologies available to store electricity. The most efficient and profitable option is very case-specific. Parameters that define the right energy storage technology are, among others, discharge rate, ramp rate, response time, power rating, efficiency, energy and power densities, technical calendar and cycle lifetime, costs and environmental concerns [41]. A general basic categorization of the currently existing technologies is shown in Figure 2.6.

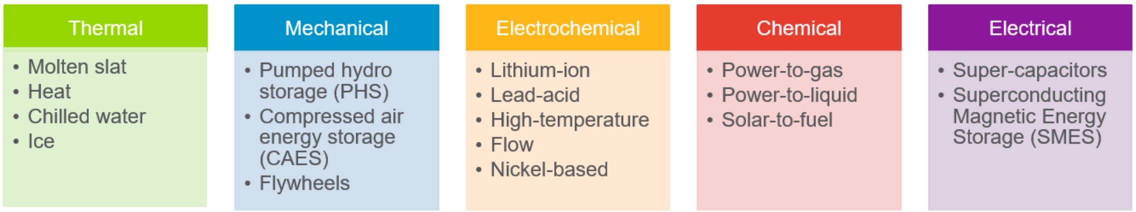


Figure 2.6: Overview of energy storage technologies [41, 10].

Since it would become too elaborate to discuss all those technologies in detail, a few will be discussed in the following subsections. The most widely used commercially available technology of grid energy storage is pumped hydro storage (PHS). Also, technologies that are suitable for large-scale application flywheels and super-capacitors. Therefore those are assessed shortly below. This research focuses on electrochemical or battery storage technologies, those will be discussed in more detail in Section 2.4.1. The chemical energy storage options are very different from the others most of them do not convert the energy back to electricity, but the energy is used as fuel. For example, power-to-gas can be applied when excess energy could be transformed into hydrogen by electrolysis of water. This hydrogen can then be used for industrial purposes or as fuel in transportation. This is also a very promising technology for future energy systems, however, is out of the scope of this research.

Mechanical storage

The PHS is very well suited for utility-scale application. Its size and capacity can range from MWh to GWh and MW to GW. However, it is strongly bound to specific locations which make it impossible to be used everywhere. Since the Netherlands have very little elevation throughout the country, pumped hydro storage is not suitable. Nonetheless, there has been experimented with pumped hydro in the country [42].

On the other hand, flywheels could be installed everywhere, but are not able to cope with large capacities and have a high self-discharge rate. In general, flywheels can provide high power capacities, up to several MW. However, their energy rating does not go up to MWh's. Therefore, they can be very efficiently used for power quality application but are less suitable for shifting peak demands. Flywheel systems are build up from bearings, the flywheel itself, power electronics and a reversible generator. All are in contained in a vacuum chamber. Electricity is used to accelerate the flywheel, which can spin with very little resistance and shear. The energy is therefore converted from electrical to mechanical energy [43].

Electrical energy storage

Supercapacitors consist of two metal foil electrical conductors with an insulator in between. Upon charging, the electricity is stored in an electrostatic field in the dielectric material. Capacitors can store just small amounts of electric energy but can provide a lot of power (up to MW's). Therefore, they are applicable for power quality services. Compared to batteries they have shorter charging times and higher power densities. Nonetheless, low energy densities and high self-discharge losses [43].

2.4.1 Battery storage technologies and applications

As discussed before, batteries have many advantages and applications. Compared to the technologies above described, batteries are classified to be able to deliver several MW's of power capacity and several MWh's of energy capacity. In this section, first, the various applications of batteries in the energy system are discussed, followed by a more in-depth description of the various battery technologies that exist.

Use cases

This subsection will first give an overview of the various possible use-cases for electricity storage. Thereafter, the choice for the focus of this research on energy arbitrage is explained.

Some general benefits of storing electricity have been addressed at the begin of this section (Section 2.4). Nonetheless, batteries specifically have very beneficial characteristics to be able to provide multiple services to the grid and its users. Therefore, this research dives into battery energy storage. The flexibility, short construction times and falling prices make them very attractive for various use-cases. Combining those use-cases can generate multiple revenue streams [36, 44]. Moreover, it has been shown that a combination of the various use-cases and services in the Netherlands leads to the most profitable storage facility. Furthermore, combining the use-cases could also reduce different risk exposures for batteries [45]. Proving a single service with an energy storage facility makes is very hard to overcome the high capital costs [27, 44, 46].

Use-cases can be divided into three general groups: power and quality regulation, energy management and bridging power. The first group refers to the stability and reliability of the power in the system. Frequency and voltage levels should always be kept within certain margins. Energy management is the concern of matching supply and demand. Lastly, bridging power are services that can be accessed when something in the system fails or when a switch between generators needs to occur for example [47].

Typical storage characteristics that determine if a storage technology is suitable for a specific use case are power and energy capacity, response time, costs, power and energy density, self-discharge rate, technical lifetime, efficiency and suitable storage duration [47]. A more exhaustive overview of the possible use-cases for utility-scale battery energy storage is listed below [10, 47, 43]:

1. Power and quality regulation:
   The power and quality regulation services, or sometimes called ancillary services, make sure that the frequency and voltage levels of the grid are kept within the safe boundaries [47]. Short response times are often a typical characteristic regarding these services, although it can vary between the specific use cases. Generally, typical requirements are power capacities up to 1 MW, response times in order of size of milliseconds (ms) and a storage duration of ms to seconds (s) or minutes (min) [43].

   In more detail, the ancillary services are voltage regulation and control, standing and spinning reserves, the security of uninterruptible power supply, fluctuation suppression and oscillation damping and frequency regulation. All make sure that energy is injected or subtracted to and from the grid to avoid fluctuations in voltage and frequency levels that could cause blackouts or damage to electric supplies [43, 47].

The need for these services is estimated to increase with the increasing VRES shares significantly [10]. Among other reasons, a cause is that storage facilities can help smoothen the output of VRES plants or provide back up services [43, 47]. However, the financial benefits of delivering ancillary services are often not clear.

2. Energy management:
   Energy has to be managed to constantly match supply and demand and balance electricity economics. Generally, energy management services require higher capacity and energy levels. Furthermore, compared to power and quality, less response time is required (in order of minutes), but longer storage duration (hours to days) [43].

   In more detail, energy management can help to shave peak demands, time-shift supply and demand, energy arbitrage, load levelling, seasonal energy storage, congestion relief in transmission systems and deferral of investments for the grid. These services enable better matching supply and demand by storing or injecting energy peak/off-peak moments. Furthermore, that results in a relieve for the transmission grid. Lastly, these services have a clear financial benefit since the electricity stored in off-peak periods is usually very cheap and can be sold at peak hours for high price [43, 47].

   Regarding increasing levels of VRES, in the energy system, energy management services can help to avoid curtailment by, for example, compensating for forecast errors or to defer large grid upgrade investments [47].

3. Bridging power:
   Bridging power services are required to back-up the energy system in case of failures or severe forecast mismatches. It helps to avoid high costs of partially running power plants, avoid high costs from forecast errors and secures power supply to electricity consumers. Typical power requirements for delivering bridging power is between 10 kW to 10 MW. Furthermore, response times are in order of seconds and discharge times of seconds up to hours [43, 47].

   Typical bridging power services are black start support, load following and ramping, contingency reserve, emergency back-up capacity and forecast hedging mitigation. These services make sure to be able to quickly restart an energy system or to keep it running during failures [43, 47].

While batteries are proven to be able to provide many of the above-described services [43, 47], most battery energy storage research focuses on the application in combination with renewable energy parks [28]. However, less focus is on independent storage facilities. For these, the major financial opportunities are regarding energy management. Since the other use-cases have no clear remuneration system. Furthermore, the fact that you can buy your electricity, in the position of a consumer when electricity prices are low and sell, when the electricity prices are high, in the role of a generator enables to benefit from the price differences. This process of arbitrage or trading electricity is therefore further investigated.

So, in this research, energy arbitrage is assessed as the main opportunity for batteries. In more detail, arbitrage is trading electricity in the markets. For example, combining activities on the spot market with the balancing market could result in generating revenues. Even as a single use-case, arbitrage has the potential to make the battery systems profitable [11, 37, 48]. So, this use-case has received a lot of attention in the research world. Arbitrage enable a storage facility to make use of the price spreads on the various markets. Furthermore, this becomes more important with growing shares of VRES in the energy system which could result in more volatile electricity prices [49].

Energy storage in the form of batteries has a lot of value on the Dutch FCR market [32]. Participation in such a capacity market is very beneficial for the business case of an ESF, because of the high upfront revenues. Moreover, it only slightly reduces the profits from other markets [44]. Furthermore, energy storage with electricity from other markets could also be profitable, like the day-ahead, intraday or FRR markets [50]. On the DAM large volumes of electricity are traded, with smaller price spreads and on the balancing markets, smaller volumes with larger price spreads are typical [33]. As an example, charging storage facilities with electricity from the spot market and discharging at the balancing market leads to significant revenue potential. A downside of this potential is that it results in a high dependency on the developments in the markets, which are known to be fast-evolving. Furthermore, its electricity prices can fluctuate a lot throughout the years. A thorough price fluctuation study of the electricity markets would be necessary for a storage facility to be sore to make a solid investment analysis [35]. Such an electricity price forecast study is outside of the scope of this research because it requires a very thorough study with a lot of insecurities and variables. The present research is based on historical price data. Therefore, before the results of the research are used to test the research method, not explicitly to calculate the specific investment risks.

Technical parameters

Batteries are cells that contain two opposite electrodes (anode and cathode) that are immersed in an electrolyte. The technology can store electric energy in chemical bonds and then release this chemical energy and convert it back to electricity. The process happens through so-called 'redox' reactions. Simultaneously a reduction reaction occurs on one electrode and an oxidation reaction on the other. It depends on the technology, materials and electrolyte how fast this can happen. An elementary image of standard battery technology is presented in Figure 2.7 (next page).

Comparing different battery technologies is mainly done by comparing several technical characteristics. The most important ones are described below:

- Power and energy rating: The energy and power rating of a battery technology sets a minimum level at which a battery operates. Lower levels of installed power and energy capacities are found not to be feasible [47].
- Energy and energy density: The power density is the amount of output a system can deliver based on the total size of the system. It is generally expressed in W/L and Wh/L for energy density [52]. In other words, for example, if the energy density of a smartphone battery is very high it defines that the battery is small and can keep the phone running for a long time. Note that a high energy density says nothing on the power density of a system. At utility-scale, these measures are usually not very important. Battery size restrictions are very relevant for

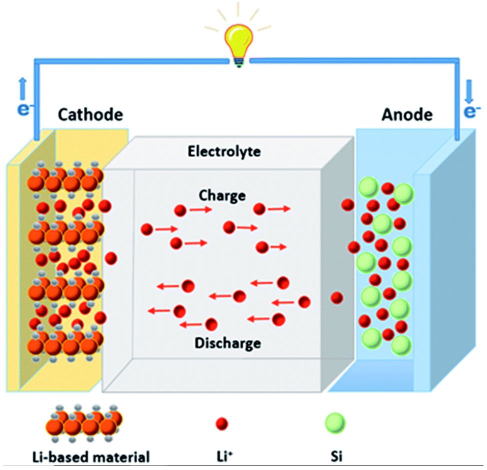


Figure 2.7: Schematic overview of the working principle of a battery [51].

portable devices for example. However, at stationary large-scale facilities, size is not often found to be a limiting measure.

- C-rate: The C-rate determines a ratio between the power and energy output of a battery system. The power output determines how fast the stored energy can be charged or discharged, while the energy capacity of a system, or volume, determines the amount of energy that can be stored. The C-rate is calculated by dividing the power capacity over the energy capacity, therefore the unit is 1/h. This means that a battery with a C-rate of 1, can fully discharge the stored energy within one-hour [52].

  Capacity loss of a battery is very dependent on the C-rate since high C-rates lead to faster fading per cycle. To be more specific, if the C-rate of a battery is high, it means that it can charge and discharge very fast. This allows the battery to quickly go through its cycles. Since capacity fade is often determined per cycle, high C-rates lead to fast capacity fade.

- Efficiency: Batteries often have a different efficiency while charging from while discharging. Therefore, usually, the round-trip efficiency is used as a measure to compare battery technologies. The efficiency determines how much energy is lost while operating the battery due to internal resistances for example.

- Self-discharge and storage duration: The self-discharge rate of a battery determines how fast the battery loses stored energy without actively discharging it. Self-discharge can originate from many sources, a common cause is a diffusion through membranes. It is usually expressed in %/day. The typical storage duration of a battery is often influenced by the self-discharge rate. If a system has a high self-discharge, it is more suitable to be used for short storage duration and the contrary for low self-discharge rates. Suitable storage duration furthermore depends on the use-case of the battery. They can range from a few seconds up to months to store energy for seasonal variations in electricity generating plants.

- SOC limits: The state of charge (SOC) is the amount of presently stored electricity in a battery as a percentage of the full capacity. Sometimes, it is also referred to as the depth of discharge (DOD). Every battery has a different resilience for operating at the very limits of the system. For example, Li-ion batteries can live longer if they are not fully charged and discharged. Therefore, those batteries have a minimum and maximum SOC limit [52].

- Technical lifetime: At the end of the technical lifetime the battery is not suitable for operation anymore and has to be replaced. The technical lifetime of a battery can be expressed in calendar lifetime or cycling lifetime. Calendar lifetime is expressed in years of operation while cycling lifetime determines how many cycles the battery can go through before reaching the 'end-of-life'. Lifetime can be influenced by many different factors among them are the average SOC or ambient temperature [53, 52].
- CAPEX and OPEX: The capital expenditures (CAPEX) and operational expenditures (OPEX) of a system determine the costs. CAPEX are costs for installation and purchasing of the system and OPEX are costs for operating the system. The CAPEX are often expressed in two manners. First, in costs per installed energy capacity (€/kWh) and secondly in costs per installed power capacity (€/kW). The OPEX are usually described as costs per installed power capacity per year (€/kWh/y).

Battery technologies can be categorised into Lithium-ion, high temperature, Nickel-based, flow and Lead-acid batteries [47]. Five techniques which are most commonly known and used, are chosen for this research; the nickel manganese cobalt oxide (NMC) Lithium-ion battery, the sodium sulphur (NaS) high-temperature battery, the Lead-Acid battery, the vanadium redox flow battery (VRFB) and the Nickel Cadmium battery. Their specific technical characteristics are shown in Table 2.1 at the end of this section. However, first, a broader explanation of each technology is given in the next subsections.

Li-ion battery

The Lithium-ion (Li-ion) battery is the most widely used battery technology. It is mostly found in portable devices, like electric vehicles or mobile phones but has also been applied stationary at grid-scale. The largest project was an 8 MWh/32 MW installation in Ohio to complement a wind farm. Currently, the just-opened Hornsdale power reserve in Australia has significantly surpassed this with an installation rated at 129 MWh and 100MW [54]. In 2017, the total installed capacity of Li-ion batteries was dominating the market with almost 60%. In the future, the Li-ion battery will probably stay the most commonly used battery for electric vehicles. However, looking at stationary applications, this is not necessarily staying the same. Nonetheless, Li-ion technology has a promising future perspective. The price of the technology is estimated to fall with about 50% by 2030, and the technical characteristics keep on improving [10, 47, 39].

One of the most successful types of Li-ion batteries is the nickel manganese cobalt oxide (NMC) type, which has a cathode consisting of Nickel-Manganese-Cobalt — combining the high specific energy of Nickel with the low internal resistance of Manganese results in a very efficient system. The anode is made of graphite, and the electrolyte is an organic liquid containing a Lithium salt [47].

Clear benefits of this battery technology are the high efficiency and energy and power density, which makes them small, which is useful for portable applications. Furthermore, the batteries usually require very little maintenance and have almost no self-discharge [39, 47].

However, it also comes with downsides. The technology is expensive compare to other storage technologies. Although compared to other battery technologies, it is one of the cheaper options. Furthermore, the batteries are not very resilient against deep discharging, so the minimal state of charge (SOC) is higher than other battery technologies, which makes the price per unit of power higher. These features make them less applicable to large-scale applications. Since Li-ion batteries are not resistant for high temperatures they require over-voltage, -current and -temperature protection [47].

Nickel-based battery

Nickel-based alkaline batteries are also one of the oldest battery technologies. Nickel Cadmium is the most commonly used type. They have been applied mainly for ancillary services like power quality control and emergency reserve for portable devices and telecommunication. They have also been used in the automotive industry. The biggest project in operation is a system in Alaska with a 27 to 40 MW power rating. Nonetheless, commercial successes of this battery technology are scarce, and they are unlikely to play a significant role in the energy storage market in the future [39, 47, 43].

The anode and cathode of the battery technology are nickel hydroxide and metallic cadmium. Furthermore, the electrolyte is an aqueous alkali solution [43].

The nickel cadmium (Ni-Cd) batteries are very robust and have high energy densities and require very little maintenance [39, 43]. Nonetheless, the batteries have relatively limited efficiency and cycle life of up to just 2500 cycles. Other significant downsides are the high installation costs and the toxicity of Nickel and Cadmium. When the battery would need to be dismantled that could cause severe danger [39, 47].

Flow battery

Flow batteries have slightly different technology than 'standard' batteries. Instead of storing the electro-active material on the electrodes, it is dissolved in the electrolyte. This electrolyte is stored in separate tanks, one for each electrode. The electrolyte is pumped to and from the tanks towards the reaction unit to charge or discharge the battery. The amount of electrolyte stored in the containers determines the energy capacity and the number of stacked cells and electrode size defines the rated power. These features make them applicable for power and energy-related applications at the same time. [10, 39, 43]. A schematic overview of the working principle of a flow battery is shown in Figure 2.8 (next page).

Flow batteries have very beneficial outlooks for the future. Significant price reductions (up to two thirds by 2030) are expected, and a lot of research is going on to improve the technical aspects. They will likely play an essential role in stationary applications once the technology is matured and commercialized. No utility-scale commercial projects have been installed yet, but centralized energy management and stationary applications are the main focus points for research. The largest project is situated in Japan with a power capacity of 3 MW aimed for peak shaving purposes. The two leading technologies are the vanadium redox flow battery (VRFB) and the Zinc Bromine flow battery, of which the first one is assessed in this research since it is the simplest and most mature one [10, 47].

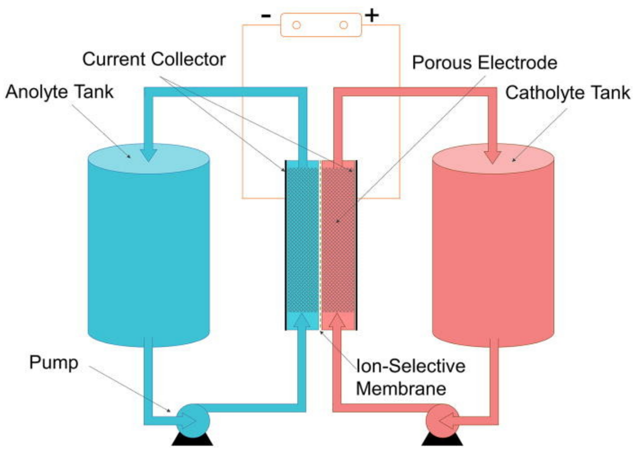


Figure 2.8: Schematic overview of the working principle of a redox flow battery [55].

The technology is precious due to scalability. The power and energy ratings can be varied independently. Furthermore, the batteries have a very high cycling life, operate at room temperature, have no SOC limits and have very little self-discharge [10, 39, 43, 47].

The flow batteries have a low energy density compared to the Li-ion battery. However, for stationary utility-scale applications, compactness of the battery is not a bottleneck. Furthermore, the efficiency of this technology is currently around 70%, which is low compared to other batteries. However, it is expected to increase up to 95% by 2030 due to technological improvements. Lastly, the cells have higher capital and operational costs which makes them more expensive than alternative technologies [10, 43].

High temperature battery

High-temperature batteries are forecast to become much cheaper in the future since a lot of research is going on and pilot projects are on their way. The capital costs are forecast to drop by almost 60% by 2030. Also, the technical performance is forecast to keep on improving in the next decade. In Japan, the batteries have been employed to provide load levelling purposes for wind farms for about twenty years. The country has an installed NaS-battery capacity of more than 300 MW. A single example project can consist of as system rated 6 MW/48 MWh. The applications make NaS-batteries the most matured technology on utility-scale [10, 39].

The two major technologies are sodium sulphur (NaS) and Sodium Nickel Chloride. The batteries make use of liquid active material and a solid ceramic electrolyte, which usually contains aluminium. The electrolyte also separates the two electrodes. The anode is usually molten sodium, and the cathode is made of molten sulphur in the NaS technology [10].

Clear benefits of the technology are the high energy density and the use of non-toxic materials. Furthermore, they have high efficiencies and inexpensive materials [10, 47]. Disadvantages originate from the corrosion issues. More research is necessary to develop coating or more robust materials to cope with this disadvantage. Furthermore, a clear point of attention is the high operating temperature which is 300°C or higher [10, 47].

Lead-Acid battery

Lastly, the oldest battery technology is assessed. The Lead Acid batteries have been applied for a wide range of use cases. Mainly microgrids, engine starting and spinning reserves were a typical application. In California, a significant project has been put into operation with a power capacity of 10 MW [39, 47].

While discharging the battery, both electrodes turn from being purely lead on one side and lead oxide on the other, into lead sulphate. Simultaneously, this process extracts the dissolved sulfuric acid from the electrolyte, which then turns to be almost only water. During charging, the process is vice versa.

Advantages are the low costs of the system, the ability to supply high pulsed power and fast response time [39, 43, 47]. But on the other hand, the batteries have relatively low life cycles and low energy densities, which makes them less favourable for time-shifting applications. Furthermore, they are not resilient for higher temperatures and therefore require a temperature control system which increases the costs [39, 43].

Comparison

How the specific technical characteristics of the five above described battery technologies compare is shown in Table 2.1. Note that many exhaustive literature reviews have already been done and that the presented number could differ from study to study. The data is taken from various references [10, 39, 41, 43, 47, 56].

Table 2.1: Battery characteristics.

	Unit	**Li-ion (NMC)**	**High T (NaS)**	**Lead-Acid**	**Flow (VRFB)**	**Ni-Cd**
Power rating	MW	0-50	0-50	0-50	0.03-50	0-40
Energy rating	MWh	0-100	0.4-600	0.001-100	0.01-10	0-6.75
Self-discharge rate	%/day	0-0.3	0-20	0.03-0.3	0-0.2	0.07-0.6
Storage duration		min - d	s - h	min - d	h - month	min - d
Efficiency	%	75-100	70-90	70-90	65-85	60-90
Lifetime	years	5-20	10-25	5-15	5-20	10-20
Lifetime	cycles	1000-20,000	1000-10,000	200-2500	10,000-100,000	1000-3500
Minimum SOC	%	0-20	0	20-50	0	0
Energy density	Wh/L	94-700	140-345	25-100	15-70	15-150
Power density	W/L	56-10,000	1.3-200	10-700	0-33.4	15-700
CAPEX (Energy)	€/kWh	170-3800	220-700	90-450	130-6000	700-2400
CAPEX (Power)	€/kW	490-4000	900-3000	260-1900	550-2500	450-1500
OPEX	€/kW/y	0-7	3.6-80	3.4-50	8-70	11-20

The table shows self-discharge rates are very small for all battery technologies. Furthermore, Li-ion shows very high efficiencies, while the flow battery is behind regarding its efficiency. The calendar lifetime of all batteries is more or less in the same range. On the other hand, cycling lifetime is very high for flow batteries and low for the Ni-Cd and lead-acid battery.

Regarding the costs of the technologies, it is observed that the OPEX are all in relatively the same range. Furthermore, lead-acid batteries show very low energy-based CAPEX. Nonetheless, the energy-based CAPEX have very wide ranges of the in the literature mentioned numbers. The power-based CAPEX show fewer differences between the different battery technologies.

2.5 Model Predictive Control

In this research, a model predictive control (MPC) method will be used to simulate optimized battery operation. MPC is a method to control a process while considering a set of constraints. Since the 1980s, MPC is used to simulate and control chemical industry plants. However, nowadays, it is also used to simulate power system balancing problems. Advantages of using MPC over other advanced control methods are the straightforward formulation, possibility to set multiple constraints, and the relatively short computing times [57]. Especially setting multiple and tight constraints is very beneficial for modelling battery storage systems since there are ramping limits, state of charge limits, efficiency losses, etcetera [58].

Furthermore, in comparison with standard feedback mechanisms, the MPC method is preferred since it enables the possibility to repeatedly optimize a system over a prediction horizon before it generates an output, see Figure 2.9. A standard feedback system can only optimize over one step at a time and with only one set of input data. In other words, the MPC schedule enables the model to take operational actions that are based on future events [28, 48, 58]. If applied to a battery arbitrage model, it distinguishes itself from standard models by comparing operation based on a set of forecast electricity prices with results based on the real electricity prices. A simple, linear optimization model allows taking only one set of electricity prices into account. The MPC model, therefore, results in a more realistic operation of the battery systems.

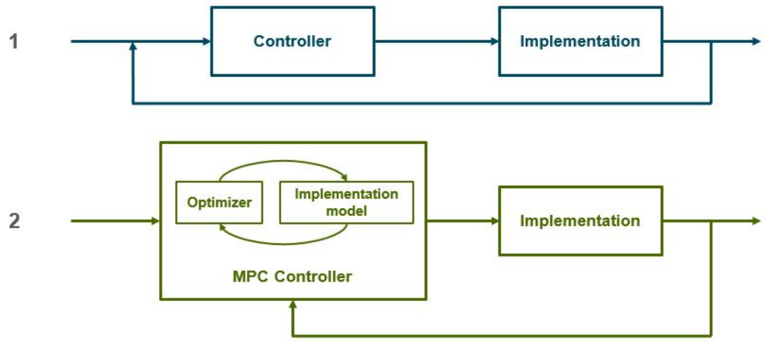


Figure 2.9: Comparison of a standard feedback model (1) and an MPC schedule (2) [28].

The MPC working principle is also shown in Figure 2.10. It follows the following steps [57, 59]:

1. At each time step, an optimization schedule is executed over a prediction horizon with an MPC optimizer. The optimizer uses input information from a predicted future and the current system state.
2. Once optimized, the output trajectory is sent to the operator.
3. The first step of the output trajectory is implemented by the operator.
4. The implemented data is used to update the current system state to calculate the results.
5. Once updated, a new time step is again modelled with the open-loop MPC optimizer. The new input for the optimizer is the updated system state and a new predicted future over the prediction horizon.

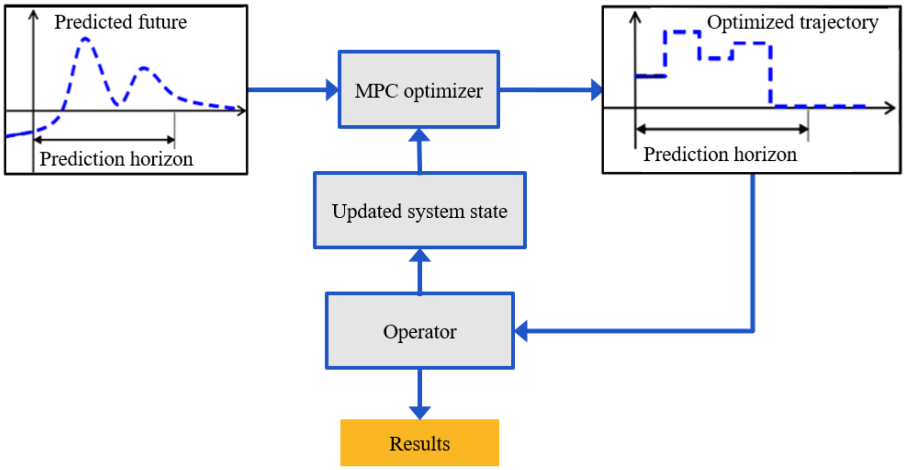


Figure 2.10: Working principle of an MPC optimizer [57].

Modelling with model predictive control can be challenging when it comes to large scale processes. However, linear programming (LP) can help to reduce the required computational performance [59]. Therefore, this research focus is on the combination of MPC with a linear optimization program.

Moreover, the MPC algorithm will be used to simulate one year of optimized energy trading on the various Dutch electricity markets with a BESF. The MPC will be able to give more realistic results then compared to a standard linear optimization model, which is used in the first part of this research. The main difference is that the MPC enables optimization over a certain prediction horizon, which could be a few hours up to a few days, while a linear program optimizes over input data of the full simulation length. For the battery model of this research, the algorithm optimizes the energy trade based on a forecast of the electricity prices over the specified prediction horizon.

Quite some research has already been done about batteries and model predictive control. An overview of the most relevant research that shows the effectiveness of optimizing the operation of battery systems with MPC from the past decade is given in Table 2.2 (next page). In literature, a clear focus is found on either modelling and operating full energy systems, including load, distribution, generation and storage, or on the combination of storage with VRES generation plants. Furthermore, literature was found on internal battery operation control with MPC. Lastly, there is also some literature focusing on the benefits of operating batteries with MPC for pure energy arbitrage purposes. Those last two subjects form the basis of this research.

When it comes to modelling energy systems, literature shows that MPC can be used for optimal operation of stand-alone micro-grids as well as on distribution level. On utility level, in [74] and [75], successfully implemented MPC models to keep forecast errors as low as possible. In [74], it is shown that storage devices could replace backup generators or balancing energy if placed close to the location of uncertainty. In [75] it is demonstrated that MPC can help to use storage for load shifting purposes while taking into account constraints on power consumption and uncertainties of weather forecasts. The combination of battery energy storage and VRES generation plants on utility-scale has been researched in [28, 58, 77] and [78]. All showed that optimizing the operation of a battery system with MPC is effective compared to perfect forecast optimization methods.

Independent battery systems operation has been modelled with MPC in several articles, as can be seen in Table 2.2. However, the focus of those optimizations is primarily the optimal use of batteries regarding their technical lifetime versus the ramp rates. Their researches did not focus on the objective to maximize revenues from energy arbitrage while using the lifetime and ramp rates as constraints.

Optimization of battery system operation for energy arbitrage with MPC specifically has been assessed in [61, 65, 66, 76] and [78]. However, only [61] and [65] looked into this for independent battery devices. The focus of their models was on the distribution level and investigated the opportunities for electricity consumers. On utility scale-independent battery storage operation for arbitrage purposes has not been simulated with MPC yet. This research, therefore, analyzes the opportunities of the promising MPC optimization for the specific purpose of utility-scale battery energy arbitrage in the Netherlands.

In the next chapter (Chapter 3) in-depth information is provided on how the models are established.

Table 2.2: Literature on MPC in combination with battery energy storage.

Reference	Storage scale	Modelling of VRES plants	Modeling energy systems	Internal battery operation	Energy arbitrage	Remarks
[60]	Distribution	X	X			Optimizing behind the meter distributed energy resources dispatch
[61]	Distribution				X	Models behind the meter storage for electricity bill reduction and arbitrage
[62]	EV/portable devices			X		Charging control to balance the state of charge
[63]	EV/portable devices			X		Optimizing charging control
[64]	EV/portable devices			X		Optimal charging control for life time constraints
[65]	Distribution				X	Models use of storage for consumers
[66]	Micro-grid		X		X	Energy management of a micro-grid
[67]	Micro-grid			X		Optimal charging to charge as fast as possible without violating the constraints
[68]	Micro-grid		X			Models optimal power flow between battery systems in a micro-grid
[69]	Micro-grid		X	X		Standalone PV-diesel-battery system
[70]	Micro-grid	X	X			Operation of a micro-grid
[71]	Micro-grid		X			Standalone PV-diesel-battery hybrid system
[72]	Undefined			X		Optimizing charging control
[73]	Undefined			X		Optimal charging control for temperature and voltage constraints
[74]	Utility	X	X			Models balancing services for VRES plants
[75]	Utility	X	X			Large scale energy smart grid system with behind the meter storage
[76]	Distribution		X		X	Arbitrage in systems with VRES generation, load and storage with net metering
[77]	Utility	X				Models balancing services for VRES plants
[58]	Utility	X				Models balancing services for VRES plants
[78]	Utility	X			X	Energy arbitrage
[28]	Utility	X				Models balancing services for VRES plants

2.6 Scientific and practical value

Consolidating the information provided in the sections above in combination with the previous work done in the field, this research focuses on optimizing battery operation for pure energy arbitrage purposes with utility-scale independent battery energy storage in the Netherlands. This leads to the following appending scientific and practical contributions, to come closer to eventually commercialized large-scale battery energy storage:

1. Simulate solely the interaction between the battery and the grid, not taking into account any generating plants or consumers. This lead to clearer insights into the added baseline value of exploiting an energy storage facility for energy arbitrage opportunities at the grid level. Furthermore, it provides insights into the maximum achievable revenues from solely energy arbitrage. This can lead as a base income that can be potentially topped up by stacking revenues from other use-cases.

2. Demonstrating the viability of using an MPC algorithm based on linear optimization to optimally operate a battery system at utility-scale.

3. Application of the considered framework on the Dutch power markets. This provides new insights into the applicability and economic viability of large scale battery energy storage in the Netherlands. In continuation of research [28], the inclusion of the FCR market and better financial modelling by taking into account the costs of financing and interest rates will bring the research closer to commercialisation.

3 Methodology

The methodology of this research is two-fold. It starts with an optimization problem regarding the system's size, technology and configuration. This will provide insights into what battery characteristics are important. Furthermore, the optimization problem will provide an upper limit of the achievable profits since it is based on a perfect foresight regarding the electricity prices. Secondly, with the battery technology that comes at as most suitable from the first part an model predictive control (MPC) operational method will be tested to simulate the operation of the battery system with a so-called 'rolling horizon'. The MPC method is found to be very promising for simulation purpose and will result in more realistic profits. Lastly, an overview is given on how the financial parameters are assessed in this research.

A list of symbols that are used in this chapter can be found in Appendix A.

3.1 Optimization

In this section, the optimization methodology for the storage system's size and configuration is described. The model optimizes the electricity flows between the BESF and the DAM and FRR markets to create the biggest revenues. A schematic overview is shown in Figure 3.1.

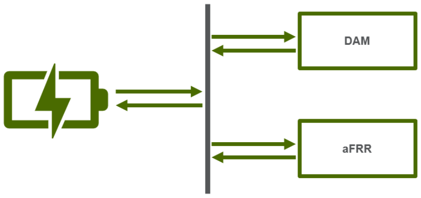


Figure 3.1: Schematic overview of the electricity flows in the optimization model [28].

The objective of the model is to identify the maximum reachable profits based on a single simulated year. The model is a mixed-integer linear optimization model in MATLAB with the Optimization Toolbox. The description of the model starts with the objective function, followed by the constraints and boundary conditions of the system, then the decision variables and lastly the required input parameters. The model is provided with perfect foresight. Therefore, real market prices of 2019 are assumed to be known upfront, leading to the maximum reachable fictional revenues. In real life, the market prices remain unknown in advance since they are based on a bidding mechanism. The resulting revenues will, therefore, be an overestimation of the actual revenues once the battery system is put into operation.

For this section, only the DAM and aFRR market are assessed. Later on, in the simulation part, also the FCR market will be considered. This choice was made since the optimization model has the purpose of finding the ideal battery characteristics. Modelling the FCR market in this part will not result in different insights, since its inclusion will have similar effects as changing the minimal SOC limit. Those effects will be shown in the sensitivity analysis of the model in Chapter 4. However, with the MPC model, the operation of the battery system is simulated, therefore the effects of extra revenues from the FCR market could have effects on the results.

Objective function

To find the maximum reachable annual profits of a BESF, the objective function of the optimization model is formulated as follows:

$$maximise\ Profit \tag{3.1}$$

The yearly profit is defined as the revenue from selling electricity minus the costs of purchasing electricity and the capital and operational costs, see the following formula:

$$\begin{aligned} Profit = & \sum_{t=1}^{t_{tot}} V_{DAM,sell,t} * P_{DAM,t} + \sum_{t=1}^{t_{tot}} V_{aFRR,sell,t} * P_{aFRR,up,t} \\ & - \sum_{t=1}^{t_{tot}} V_{DAM,buy,t} * P_{DAM,t} - \sum_{t=1}^{t_{tot}} V_{aFRR,buy,t} * P_{aFRR,down,t} \\ & -(CAPEX_{MWh} * V_{max} + CAPEX_{MW} * Power\ Cap) * \frac{t_{tot}}{LT} \\ & -OPEX * Power\ Cap * \frac{t_{tot}}{no.\ time\ steps\ per\ year} \end{aligned} \tag{3.2}$$

The first two terms in this formula represent the revenues that come from the volumes of electricity sold on the DAM and the aFRR markets multiplied by the respective market price of that time slot. The costs originate from buying power on those markets and from installing and operating the facility. The second two terms of the equation represent the costs of purchasing electricity. The CAPEX, the third term of the equation, is determined by the installation costs per amount of energy capacity (volume) and power capacity, relative to the technological age of the facility. The last term of the equation, the OPEX, is a yearly cost (including transmission grid tariffs) relative to the power capacity of the facility. The extra component of t_{tot} divided by the number of time steps in a year is added to cope with the time dependency of the OPEX (35040 time steps of a quarter-hour is one year).

This objective function makes sure that the model optimizes by minimizing the electricity purchasing costs and maximizing the revenues from selling electricity while satisfying the below-described constraints.

Constraints and assumptions

The objective function, to maximize the profit, is bound by the following set of constraints and assumptions:

1. The objective function aims to optimize the annual profit, so the optimization runs for one whole year. Since the FRR market is operated every quarter, the simulation length (t_{tot}) will be 35040 ($= 365\ d * 24\ h * 4\ q$) time steps long.

   Simulation of one year is chosen because longer periods lead to extremely long computing times.

2. Since the model is designed with a separate inflow and outflow to and from the three different elements of the system (see Figure 3.1), all electricity flows cannot be lower than zero. Hence:

$$V_{in,t},\ V_{out,t},\ V_{DAM,sell,t},\ V_{DAM,buy,t},\ V_{aFRR,buy,t},\ V_{aFRR,sell,t} \geq 0 \tag{3.3}$$

3. The law of conservation of energy does not allow creation or loss of energy. However, the energy that goes through the battery is subject to an efficiency loss and therefore the sold electricity is not the same as the amount of discharged electricity and ditto for charging and buying electricity. Hence a constraint is needed that limits the energy flowing in and out of the storage facility to be equal to the energy sold or bought on the two markets. Furthermore, the out- and inflow of electricity to the storage facility are subject to the efficiency loss. These two statements lead to the following constraints:

$$V_{out,t} * \eta_{disch} = V_{DAM,sell,t} + V_{aFRR,sell,t} \tag{3.4}$$

$$V_{in,t} = (V_{DAM,buy,t} + V_{aFRR,buy,t}) * \eta_{ch} \tag{3.5}$$

   Furthermore, the charging and discharging efficiencies are assumed to be equal and therefore:

$$\eta_{disch} = \eta_{ch} = \eta \tag{3.6}$$

4. The cable that connects the battery system to the grid, has a certain maximum capacity of electricity it can let through. The maximum size of the cable is defined to be the same the maximum volume of the facility. This definition assumes that any required cable capacity can and will be installed by the TSO, which in reality is not necessarily the case. Nonetheless, the cable size should not be a limiting constraint for the optimization problem. This assumption is formulated by the following equation:

$$V_{max} = CBCP \tag{3.7}$$

   However, it provides the system with the constraint that total electricity flowing in or out of the storage facility at one time step cannot be bigger than the maximum cable capacity. Since the cable capacity is the same as the maximum size of the battery, it implies that the battery could, if ramping limits allow, fully charge or discharge in one time step. This is formulated in the following formula:

$$-CBCP \leq V_{out,t} - V_{in,t} \leq CBCP \tag{3.8}$$

Additionally, this equation determines that simultaneous buying and selling within one time step is allowed in the model. For example, electricity bought on the DAM can be directly sold on the FRR market. In reality, this feature will be limited since the trading schedules of the two different markets are different.

5. An extra constraint on the maximum in- or outflow of electricity of the ESF is the maximum ramping rate. A ramping rate is the maximum amount of electricity that a system can deliver in one time step. Since batteries generally have very short response times, they can quickly switch between charging, discharging and doing nothing. Nonetheless, there is a maximum installed power capacity. The ramp rate is defined by the C-rate of the battery and the total installed volume. The C-rate on its turn is defined by dividing the installed power capacity by the installed volume. Lastly, the model operates with 15 minute time steps, so the C-rate is multiplied with a factor 0.25 since 15 $min = 0.25$ h to come to the maximum ramp rate:

   $$R = V_{max} * C\text{-}rate * 0.25 \tag{3.9}$$

   $$C\text{-}rate = \frac{Power\ Cap}{V_{max}} \tag{3.10}$$

   High C-rates result thus in the allowance of higher electricity flows per time step which is a favourable characteristic for energy arbitrage purpose since it allows for more cycling. However, more cycling leads to faster capacity fade, which is explained in constraint 8.

   Furthermore, the ramp rate is assumed to be symmetrical and therefore the maximum ramp 'up' and 'down' are equal:

   $$V_{in,t},\ V_{out,t} \leq R \tag{3.11}$$

6. The state of charge (SOC), which is the amount of electricity stored in the battery system, at a particular time step (*V(t)*) is defined as the SOC of the previous time step plus the amount of electricity bought and flowing into the system and minus the electricity flowing out of the system, the sold electricity:

   $$V_t = V_{t-1} + V_{in,t} - V_{out,t} \tag{3.12}$$

7. The state of charge (SOC) of the battery should remain within the maximum and minimum allowable values. Not all batteries technologies are designed to fully charge or discharge every cycle. Some technologies, for example, the Li-ion battery, suffer from severe capacity fading if they operate at the upper or lower limits of their installed volumes. In the presented model, the SOC limits are defined as a percentage of the total volume of the system.

   Furthermore, all battery technologies suffer from some kind of capacity fading due to cycling. How the capacity fade is defined, follows in the next constraint (8). For the state of charge of the battery however, the capacity fade influences the upper limit of the available battery volume.

   Therefore, the state of charge of the battery at a certain time step is defined with the following formula:

   $$V_{max} * SOC_{min} \leq V_t \leq V_{max} * SOC_{max} - Cap.\ fade_t \tag{3.13}$$

In reality, the upper and lower state of charge limits will not be as 'hard' as assumed in this optimization model, but in the design phase that cannot be assumed [67]. This will be further explained in the Discussion, in Chapter 5.

8. The above-mentioned capacity fade, or capacity loss, of the system, is caused by the operation of the battery system. Many different factors can play a role in causing this capacity loss. Chemical, as well as mechanical degradation, play their parts. Among the influencing factors are the ambient temperature, C-rate and the average SOC. In this discussed optimization model, the capacity fade is in principle based on the number of cycles that the battery went through. Therefore, especially the C-rate plays an important, but an indirect, role in defining the capacity loss. As earlier discussed, high C-rates allow for faster cycling of the battery system which is favourable for trading electricity. However, it leads to faster capacity fade according to the following formula:

$$Cap.\ fade_t = \frac{\%_{Cap.fade} * V_{max}}{CL} * \frac{\sum V_{in,t}}{V_{max}} \tag{3.14}$$

In more detail, in this formula, the first term defines the capacity that fades per cycle. It is assumed that the total faded capacity is evenly distributed over all cycles of the entire cycling lifetime of the battery. The $\%_{Cap.fade}$ represents the assumption that if a certain percentage of the initial total volume is faded, the batteries are at the end of their technical life and will have to be replaced. Furthermore, the second term of the equation defines the number of cycles that have passed. One cycle of the battery is determined to be one full charge. So, the number of cycles is defined by the sum of all charged electricity (V_{in}) divided by the total battery volume (V_{max}).

However, the end of life based on the calendar instead of the cycles might be reached before the maximum amount of cycles is reached. 'End of life' could either be the end of the calendar life or the cycling lifetime. Therefore, the capacity fade is also bound by the following formula:

$$Cap.\ fade_t \leq \%_{Cap.fade} * V_{max} * \frac{t_{tot}}{LT} \tag{3.15}$$

This equation defines the assumption that the total faded capacity is evenly distributed over all time steps of the entire calendar lifetime of the battery. Together, the two equations state that in principle, the capacity fade is defined based on the technical cycling life unless it exceeds the maximum capacity fade per calendar lifetime.

9. Since the self-discharge rate of all battery technologies is approximately zero (see Table 2.1), this is assumed to be negligible in the calculations. This assumption can be defended by the fact that energy arbitrage, which is the purpose of this model, is characterized by rapid cycling behaviour. On the contrary, self-discharge becomes more relevant when batteries remain inactive for long periods.

Variables and parameters

Based on the above described constraints and assumptions, the algorithm will find an optimal value for the decision variables. Those are the variables that have to be optimized by the model and are listed below:

- The sold or bought volumes on the DAM and aFRR markets ($V_{DAM,sell,t}$, $V_{DAM,buy,t}$, $V_{aFRR,sell,t}$ and $V_{aFRR,buy,t}$): These are the key variables that will determine the revenues of the system. The model considers the electricity prices on the markets and decides when to buy or sell electricity to retrieve the highest margins.

- The charged and discharged volumes of electricity for every time step have to be decided ($V_{in,t}$ and $V_{out,t}$): Those will be similar to the sum of the sold and bought volumes of electricity, however, the efficiency losses will be taken into account. Depending on how much electricity is sold, the outflow of the battery system is defined and vice versa for the inflow.

- The state of charge (V_t) which is the charged volume of the BESF at time step t: This variable follows from the above described decision variables. The state of charge is updated for every time step according to how much electricity is flowing in or out.

- The sum of all charged electricity at time step t ($\sum V_{in,t}$): This decision variable is necessary to account for the capacity fade of the system. The number of cycles that have passed is expressed by how much electricity is charged in total at a certain time step. Every full charge accounts for one cycle.

- The capacity fade of each time step of the battery system (*Cap. fade*): Based on the total amount of electricity fed into the system, the capacity fade is calculated. A certain amount of energy capacity of the system is lost upon every cycle. This is the key decision variable that withholds the algorithm to keep on charging and discharging. It, therefore, makes sure that the capacity of the system is optimally used over the whole technical lifetime.

Lastly, the input parameters required to run the above-described MATLAB optimization model are the technical characteristics, market prices and the installation costs of the facility. The technical characteristics that are used can be found in Table 4.1 in the next chapter. Furthermore, information on the market price data is given in the next section (Section 4.1.1).

Monte Carlo simulation

Since the above-described optimization model has many different parameters which have different influences on the outcomes, a Monte Carlo simulation has been used in this research to simulate the effects of varying volume and capacity of the battery system.

Furthermore, it has been shown that fixing either the power or the energy capacity leads to suboptimal results. This can be explained that by the fact that the ratio between the two, the C-rate, directly influences the profitability of a storage system [79]. To simulate the sensitivity of the system for both the power capacity and energy capacity, the Monte Carlo method is used.

A Monte Carlo simulation is based on repeating a simulation many times with random, uniformly distributed input parameters. The results allow for statistical analysis of the random experiments. The statistical analysis that follows is based on the 'law of large numbers', which states that the average result of a large number of experiments, is the most likely result of the next experiment. Therefore, the more simulations are done, the larger the confidence interval of the results [80].

The Monte Carlo simulation in this research simulates the battery system over a half year instead of a full year to reduce computing time. Furthermore, the random input parameters are the battery volume and capacity.

3.2 Simulation with Model Predictive Control

The above-designed optimization model is an adequate way of determining the optimal battery configuration. However, the result is an overestimation of the profitability of the system because known real electricity prices are assumed to be available for a whole year. Nonetheless, the optimization resulted in the most beneficial battery technology with its specific technical characteristics. Now, an operational tool is implemented to give a more realistic result for the operation of the battery system. The tool will determine an optimized trading schedule for the storage facility. This is done with a model predictive control (MPC) algorithm. In principle, the simulation of the BESF operational model with MPC is very similar to the linear optimization described above (section 3.1). A description of what MPC is and how it in principle works, is described in Section 2.5. This section will describe how the MPC method is used for energy arbitrage purposes of batteries. Because of the similarities with the above-described optimization model, the focus of this section is on the differences.

In both models, the objective to maximize the profits of the battery system by trading electricity on the DAM and FRR market still holds. However, three major changes have been made to implement the MPC. The three changes are listed below:

1. The optimization horizon is not the whole year, which was the case in the above described linear optimization, but is bound by a certain forecast horizon. That means that for every simulation time step, the model will optimize over the predefined forecast horizon, which can be a few hours or days. The optimized trading strategy that results will update and overwrite the trading strategy from the previous step. This limitation on the forecast horizon leads to more realistic operational results for the battery system since electricity prices, in reality, are not known upfront and need to be forecast. To implement this method a set of forecast electricity prices is required. How the forecast electricity price series are obtained will be discussed later in Subsection 4.2.1. Furthermore, to implement this limited forecast horizon, two timelines have to be defined. One determines the moment in time of the forecast and the other determines the actual time step of the simulation.
2. Trade at the FCR market is added. As described before, the inclusion of the FCR market had no added value in finding the ideal battery characteristics. However, when simulating the operation of the model, the FCR market can potentially add value to the battery system. To include the FCR market in the algorithm, a certain share of the battery power capacity has to be always available. For the optimization of the trading strategy, it limits the energy available for the DAM and FRR markets, but it provides an extra revenue stream. It is assumed that any reserved capacity for the FCR market will be accepted by the market operator. Therefore, it will always result in revenues for the facility, while in real life this is not necessarily the case. In the simulation, the optimal share of reserved capacity for the FCR market will be researched.

3. In the MPC model, no capacity fade is assumed for the sake of shorter computing times. This assumption can be justified by the fact that only one year of operation is simulated in which only a very small share of the capacity fade will be lost. The effects of exclusion of the capacity fade on the profits will be researched in the sensitivity analysis of the linear optimization model. Furthermore, to research the effects of capacity fade on longer operational periods, a 'final' year will be simulated as well. This will be the last year of the technical lifetime of the battery system and thus has already a significant share of lost capacity.

Similar to the optimization method described in Section 3.1, the MPC model works with a linear optimization programme within MATLAB. The simulation, however, uses a 'for-loop' that executes the optimization model at two levels. First, 'online', by optimizing the FRR bidding strategy at every hour. And second, 'day-ahead' at noon every day, it executes the DAM optimization model. Such a sequence has been suggested in [74] and [28].

The operational scheme of the MPC algorithm is shown in Figures 3.2 and 3.3. The figures show a repetitive schedule for every day and every hour in the simulation. In Figure 3.2, it is shown that at the first hour (hour 0), the algorithm obtains a series of forecast price data of the FRR for the following 6 hours. At the same time, the optimization of the trading strategy for the aFRR market is optimized over the same forecast horizon of 6 hours. The first hour of this trading strategy, which states when and how much electricity to buy or sell for every quarter of the hour, is implemented. So, the first hour of the optimized strategy is locked and settled. In the next hour, a new trading strategy is optimized over a new set of forecast electricity prices for the next six hours. Again only the first hour is implemented. This is a repetitive scheme for every hour of the year.

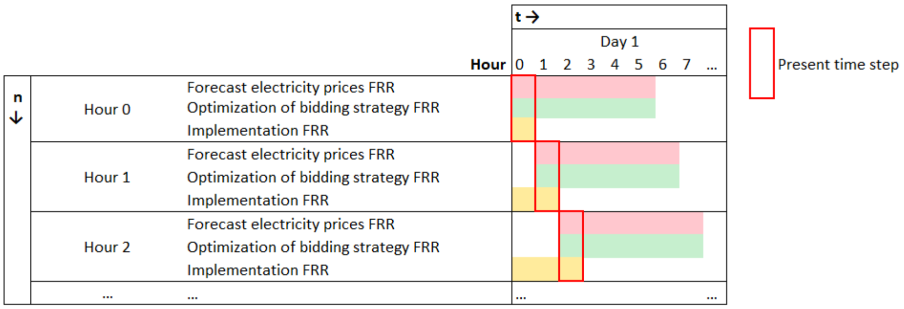


Figure 3.2: Optimization schedule of the MPC model for the FRR-market.

Regarding the operational schedule of the DAM, a different pattern is used, see Figure 3.3 (next page) At noon of the first day, the first DAM trading strategy is optimized. It obtains a price forecast for the following 2.5 days. Then at the same time, the bid strategy is optimized for the same forecast horizon of 2.5 days. Since bids for the DAM have to be made one day in advance, the actual implementation of the optimized trade strategy is for the whole day, every quarter-hour, of the next day. On the next day, at noon again, a new strategy is optimized for the day thereafter. Note that it is assumed that no electricity is traded on the DAM on the first day of the simulation. That is a result of the fact that the first optimization is initialized at noon on the 1st of January. Therefore, no trading schedule can be optimized for this first day.

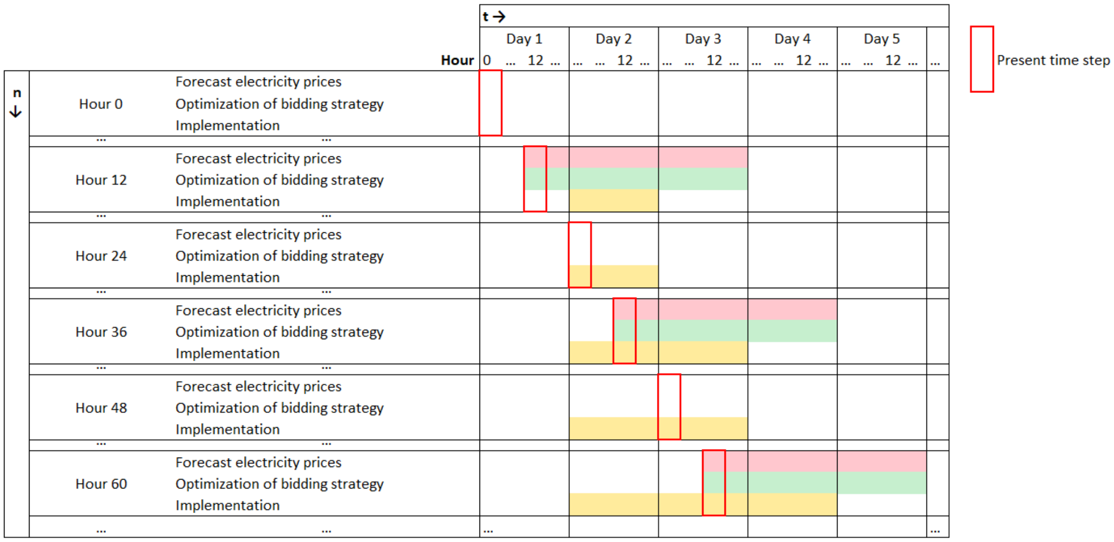


Figure 3.3: Optimization schedule of the MPC model for the day ahead market.

To further elaborate on this, the operational flow chart of the MPC model is shown in Figure 3.4 (next page). The simulation starts with implementing the initial parameters like, among others, the state of charge and the forecast price series. Next up, it algorithm checks whether its noon. If it is noon, the DAM and aFRR functions are both executed. At all other hours during the day, only the aFRR module is performed. The newly optimized parameters are then fed back in to update the start phase with new initial settings for the next simulation step. Furthermore, at every iteration, after the execution of the FRR module, the first hour of the optimized schedule is implemented. The optimized bids of this first hour are then used as input for the revenue calculations. However, while the bids were optimized with a forecast price series, the revenues are calculated with the real electricity prices. Therefore, not all bids will give the benefits that were estimated for resulting in less optimal, but more realistic results.

The separate mathematical optimization models for the DAM and FRR are described in the following two sections. As mentioned before, in principle are the individual FRR and DAM function the same as the optimization model of Section 3.1. In the following sections the differences, other than the length of the optimization horizon, will be described. In those sections, since the MPC model uses two different time horizons, a different notification is needed. Every loop, or simulation step in the MPC is noted as n, so $n \in 1, 2, ..., n_{tot}$ in which n_{tot} is 35040 time steps for a one year simulation of every quarter. Within the optimization functions t is used to identify the time step ($t \in 1, 2, ..., t_{tot}$). t_{tot} depends on the forecast horizons of each market. In short, t is the time step within the forecast horizon and n is the present time step of the simulation.

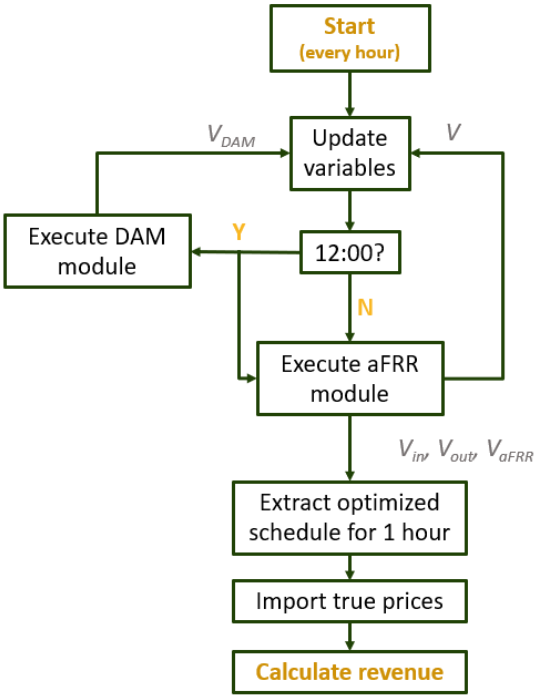


Figure 3.4: Flowchart of the MPC model.

3.2.1 FRR function

The basis of the objective function of this bidding strategy optimization is the similar to the optimization model of Section 3.1. However, the electricity prices provided to the algorithm are the forecast electricity prices instead of the real data. See below:

$$maximize\ Revenue \tag{3.16}$$

$$\begin{aligned} Revenue = &\sum_{t=1}^{t_{tot}} V_{DAM,sell,t} * Forecast\ P_{DAM,t} + \sum_{t=1}^{t_{tot}} V_{aFRR,sell,t} * Forecast\ P_{aFRR,up,t} \\ &- \sum_{t=1}^{t_{tot}} V_{DAM,buy,t} * Forecast\ P_{DAM,t} - \sum_{t=1}^{t_{tot}} V_{aFRR,buy,t} * Forecast\ P_{aFRR,down,t} \\ &- (CAPEX_{MWh} * V_{max} + CAPEX_{MW} * Power\ Cap) * \frac{t_{tot}}{LT} \\ &- OPEX * Power\ Cap * \frac{t_{tot}}{no.\ time\ steps\ per\ year} \end{aligned} \tag{3.17}$$

Regarding the constraints of the FRR model, one big difference can be observed. Since no capacity fade is assumed, the constraint for the upper limit of the battery level is changed. Furthermore, the FCR market is now included in the model. Therefore, the minimum SOC changes. The upper and lower limits of the battery level are now defined as follows:

$$V_{max} * (SOC_{min} + \%_{FCR}) \leq V_t \leq V_{max} * SOC_{max} \tag{3.18}$$

In this equation, $\%_{FCR}$ is the reserved volume of the battery capacity as a percentage of the total installed volume. Since the battery volume is defined in MWh and the FCR market prices in MW, this has to be converted. Furthermore, there is a limit in the maximal capacity that can be offered to the market. The reserved power capacity of the battery for the FCR market is defined to be the same or smaller than the rated power capacity of the battery system. Lastly, the FCR market requires the electricity supplier to be able to supply the contracted capacity for at least 15 minutes, and after that, the supplier has two hours to restore [30]. Since the model is defined in 15 minute time steps, the power capacity should be multiplied by 0.25 to find the needed energy volume to supply this ($1\ q = 0.25\ h$). Therefore, the percentage of the reserved amount for the FCR market ($\%_{FCR}$) is defined with the following equation:

$$\%_{FCR} = \frac{FCR_{capacity} * 0.25}{V_{max}} \tag{3.19}$$

Next, the decision variables of the model are the sold and bought volumes on the FRR market ($V_{FRR,sell,t},\ V_{FRR,buy,t}$), the charged and discharged volumes ($V_{in,t},\ V_{out,t}$) and the state of charge (V_t). The sold and bought electricity volumes on the DAM are not decision variables but are directly extracted from the results of the DAM function.

Lastly, the required input parameters of the FRR function are, therefore, next to the technical battery characteristics and costs, also the sold and bought DAM volumes for the specific hour. Moreover, the required inputs are the forecast FRR electricity prices, the SOC at the end of the previous hour in the simulation, the reserved FCR volume and the length of the optimization horizon.

3.2.2 DAM function

In addition tot the FRR description above, a few other differences compared to the optimization model of Section 3.1 can be observed in the DAM function. The difference in objective function of the DAM module is the absence of the traded volumes on the FRR market. Since the DAM bidding strategy optimization has a longer forecast time horizon then the one for the FRR, no FRR trading data is available yet. This can also be seen in Figures 3.2 and 3.3. Therefore, the objective function is reduced to the following:

$$maximize\ Revenue \tag{3.20}$$

$$\begin{aligned} Revenue = &\sum_{t=1}^{t_{tot}} V_{DAM,sell,t} * Forecast\ P_{DAM,t} - \sum_{t=1}^{t_{tot}} V_{DAM,buy,t} * Forecast\ P_{DAM,t} \\ &-(CAPEX_{MWh} * V_{max} + CAPEX_{MW} * Power\ Cap) * \frac{t_{tot}}{LT} \\ &-OPEX * Power\ Cap * \frac{t_{tot}}{no.\ time\ steps\ per\ year} \end{aligned} \tag{3.21}$$

Moreover, the absence of the FRR bidding strategy also influences the constraints of the model. Therefore, the constraints that bound the DAM objective function are described with the following equations:

$$V_{out,t} * \eta_{disch} = V_{DAM,sell,t} \tag{3.22}$$

$$V_{in,t} = V_{DAM,buy,t} * \eta_{ch} \tag{3.23}$$

As a result, the decision variables for this DAM function are the sold and bought volumes on the DAM ($V_{DAM,sell,t}, V_{DAM,buy,t}$), the charged and discharged volumes ($V_{in,t}, V_{out,t}$) that follow from the traded volumes and the resulting state of charge (V_t). The optimized trading strategy on the DAM ($V_{DAM,sell,t}$ and $V_{DAM,buy,t}$) will be used as input for the FRR function.

Required input parameters are the forecast market prices for the DAM, the technical battery parameters and their costs, similar to Section 3.1, the SOC at the end of the previous hour, the total volume of charged electricity at the end of the last hour, the reserved FCR volume and the length of the optimization horizon.

3.2.3 Profit calculation

Last in the description of the MPC model is the profit calculation. The yearly profits can be calculated based on the implemented trading strategies of the DAM and FRR and the revenues from the FCR market. As described earlier, the resulting profits are calculated with the real electricity prices, while the bidding strategy is optimized with forecast electricity prices. This difference will have sub-optimal, but more realistic results.

The yearly profit is calculated similar to as described in Section 3.1, however, with the addition of the FCR revenues. The equation is shown below.

$$\begin{aligned} Profit = \sum_{n=1}^{n_{tot}} V_{DAM,sell,n} * P_{DAM,n} + \sum_{n=1}^{n_{tot}} V_{aFRR,sell,n} * P_{aFRR,up,n} \\ - \sum_{n=1}^{n_{tot}} V_{DAM,buy,n} * P_{DAM,n} - \sum_{n=1}^{n_{tot}} V_{aFRR,buy,n} * P_{aFRR,down,n} \\ + \sum_{z=1}^{z=365} FCR\ Cap * P_{FCR,z} \\ -(CAPEX_{MWh} * V_{max} + CAPEX_{MW} * Power\ Cap) * \frac{n_{tot}}{LT} \\ -OPEX * Power\ Cap * \frac{n_{tot}}{no.\ time\ steps\ per\ year} \end{aligned} \tag{3.24}$$

Note that the FCR market operates a daily price system, hence uses a different time indicator ($z \in 1, 2, ...365$).

3.3 Economic assessment

In the above-described models, the annual profits have been calculated with a fairly simple calculation, which can lead to over-estimations of the profitability of the battery system. In the models, the annual capital costs are calculated by dividing the total capital costs by the technical calendar lifetime. This method does not take into account any costs of financing. The basic profit function used is the following:

$$\begin{aligned} Annual\ profit = {} & Revenue\ from\ sold\ electricity + Costs\ of\ bought\ electricity \\ & -\frac{CAPEX}{LT} - OPEX \end{aligned} \tag{3.25}$$

In this equation, it is assumed that the OPEX, CAPEX, revenues and profits are equal throughout the whole technical life to the storage facility. Moreover, the elementary assessment of the economic viability of the BESF is calculating the annual profit margin. It is the percentage of the investment that is earned back with the yearly profits. It could immediately define how many years it will have to take to earn back the investment fully. The equations are as follows:

$$Annual\ profit\ margin(\%) = \frac{Profit}{Total\ investment} * 100\% \tag{3.26}$$

$$Pay\ back\ time(y) = \frac{100\%}{Annual\ profit\ margin} \tag{3.27}$$

However, as explained above these calculations do not take into account any costs of financing. Therefore, the results will be an over-estimation of the reachable financial results. To calculate the costs of financing, the total debt must be known as well as the interest rate on the loan and the length of the loan, which is assumed to be the full lifetime of the battery system, see the equation below:

$$Yearly\ cost\ of\ financing = \frac{r}{1-(1+r)^{-LT}} * CAPEX * Debt\ share \tag{3.28}$$

In this equation, r is the annual interest rate on the debt, LT is the technical calendar lifetime of the battery system in years and *Debt share* is the share of the capital costs that required external financing.

3.3.1 LCOS

Furthermore, to compare the profitability of storage systems, the levelised cost of storage (LCOS) is used. It is a measure that defines the discounted costs of storage per unit of discharged electricity in €/MWh. The LCOS allows for easier comparison for various technologies [81]. The measure is derived from the more commonly known levelised cost of electricity (LCOE). While the LCOE is used to compare the costs of energy generators, LCOS is adapted for storage which neither generates nor consumes energy [53]. Although it must be noted that not all compared technologies might be able to capture the same price differential.

The LCOS is defined as the sum of the initial investment costs (CAPEX) and discounted annual costs (OPEX) divided by the total annual energy output of the battery system ($\sum V_{out,t}$) [81], see Equation 3.29.

$$LCOS = \frac{CAPEX + \sum_{t=1}^{t=LT} \frac{OPEX_t * \frac{t}{LT}}{(1+i)^t}}{\sum_{t=1}^{t=LT} \frac{V_{out,t}}{(1+i)^t}} \tag{3.29}$$

In this equation, t is the time in years. All simulations run over one year, so $t = 1$. This also holds that it is assumed that the OPEX, CAPEX, revenues and profits are equal throughout the whole technical life to the storage facility. Lastly, i is the discount rate.

The discount rate defines if an investment is more profitable compared to other possible investments. It is assumed to be approximately the same as the weighted average cost of capital (WACC). These financing costs originate from the debt and equity that is necessary to do the investment. The value reflects the risk and returns for the future. The WACC is the minimum return that must be made to satisfy all debt and equity costs [82]. The WACC can be calculated with the following formula:

$$WACC = \frac{E}{E+D} * R_e + \frac{D}{E+D} * R_d * (1-T) \tag{3.30}$$

In this formula, E is the value of the equity and D the value of the debts. R_e and R_d are the costs of these equities and debts, respectively. The first term of this equation represents the percentage of equity and the second term defines the percentage of debts. Lastly, T is the tax rate in percentage. The tax rate can be subtracted from the debts. Therefore, the second term in the WACC equation is multiplied with one minus the corporate tax. The final WACC value that results, is used as the discount rate in the LCOS calculations.

In the next chapter, the results of the more comprehensive profit calculation can be found as well as the value of the LCOS for the various battery technologies, in Section 4.3.

4 | Results

This chapter discusses the results of the executed research based on the previously described methods. First, data and insights are provided from the results of the optimization model. Second, the results of the simulation with MPC are provided. Lastly, the results of the more comprehensive financial assessment are presented.

4.1 Optimization

This section discusses the results of the optimization method to define the ideal battery characteristics and to define what type of battery is the most beneficial. The section starts with providing information regarding the input of the algorithm. Second, the most important results of the sensitivity analysis are shown. Thirdly, the different technologies are compared based on the results of the Monte Carlo method. Lastly, the effects of optimizing over a single year of operation are presented.

4.1.1 Input data

As described in the methodology, a certain set of input parameters is required to run the model. First the price data of the various markets and second the technological characteristics of the different types of batteries.

The technical input data of the various battery technologies is shown in Table 4.1 (next page). The chosen input parameters are based on the previously described technical parameters of the five different battery technologies in Table 2.1. It must be noted that the provided energy and power ratings in Table 2.1 are no limits, but provide a minimum level. Therefore, they could be exceeded in this research because the model is on utility-scale. It is assumed that if the modelled volume or power capacity of the battery exceeds the rated power or energy mentioned in Table 2.1, it has no significant impacts on the CAPEX or OPEX. Moreover, it has been assumed that the costs of the battery systems and that those scale linearly with size. In real life, this is not the case and often it is noted that the CAPEX per installed energy volume or power capacity decreases when the system gets bigger. That is a result of the fact that for example construction equipment does not need to be doubled upon doubling the battery size. Therefore, this assumption is likely to lead to an overestimation of the system's costs as the systems get bigger.

Table 4.1: Battery characteristics input data for the optimization model. Note: OPEX is defined including the grid tariff of 36.56 €/kW/y [56]

	Unit	**Li-ion (NMC)**	**High T (NaS)**	**Lead-Acid**	**Flow (V)**	**Ni-Cd**
Efficiency	%	95	80	80	72	75
Lifetime	years	20	25	15	20	20
Lifetime	cycles	3500	10,000	2500	50,000	3500
Minimum SOC	%	40	0	20	0	0
CAPEX (Energy)	€/kWh	430	460	270	616	1550
CAPEX (Power)	€/kW	492	1950	1080	686	975
OPEX	€/kW/y	43.56	78.36	63.26	44.56	52.06

For the Li-ion and flow battery parameters, the TenneT storage tool was leading in deciding the parameters [56]. Except for the minimum state of charge of the Li-ion battery. This has been changed to 40%. Since Li-ion batteries are generally operated between a SOC of 20% and 80%, there is 40% of the battery energy capacity unused [83]. The maximum SOC for all battery technologies is set at 98%. Therefore, the minimum SOC of the Li-ion battery has been raised from 20 to 40%. Regarding the flow battery, also one change has been made compared to the TenneT Storage Tool data. The tool had a very optimistic cycle life for the battery, therefore a more moderate, but still optimistic value of 50,000 cycles has been used.

For the other technologies, the most optimistic values of the found parameters in literature were used for the minimal SOC and calendar and cycle lifetime. Note that this could result in optimistic results regarding business case opportunities. However, technical and financial improvements for battery technologies happen at a fast pace and are forecast to keep on improving [10]. For the efficiency, the average value is taken between the highest and lowest values found in the literature.

Regarding the costs of the systems, the capital costs of an energy storage facility consist of the purchasing, constructing and delivering of the storage unit, the balance of power costs and cost for the power conversion system. The power conversion installation costs are usually expressed in €/MW. The other capital costs are energy-based and expressed in €/MWh. In this research, the CAPEX do not include grid connection costs, cost of re-powering the assets or decommissioning costs.

The OPEX are costs related to operation and maintenance. The OPEX are defined in €/MW/y [39]. The OPEX do contain a network tariff, which is set at 36.56 €/kW/y [56]. Again for the Li-ion and flow batteries, the TenneT Storage Tool was leading in choice of parameter. For the other technologies, the OPEX were defined as the average value of ultimate values found in the literature plus the grid connection costs.

Other input parameters that have been used are listed below:

- The initial state of charge of the battery system is set at 50% of the total storage capacity. This assumes that the amount of electricity presently stored in the system at $t = 0$ did not cost anything. In reality, upon installing the BESF, the initial state of charge will be zero.

However, to imitate the continuous operation of the battery system, it is more realistic to have some electricity stored already at the beginning of the year.

- The self-discharge of all battery technologies is assumed to be zero since all are very small as can be seen in 2.1.
- The 'end-of-life' capacity fade ($\%_{Cap.fade}$) is defined as 35% of the total volume of the facility for all technologies [84]. This represents the assumption that if 35% of the initial total volume is faded, the batteries are at the end of their technical life and will have to be replaced.
- The maximum SOC at the start of the simulation is set at 98% for all techniques. The minimum SOC, however, can vary according to the varying battery technologies.

Market price data

The market prices are actual data of the ENSTO-E Transparency Platform [33]. Data has been extracted for the years 2016 to 2019.

Since the model is on a quarterly basis and the electricity prices of the DAM are on an hourly basis, it is assumed that the hourly rates are constant over the four quarters of every hour. Furthermore, if the DAM market price was found to be below zero, the price was set to zero. That was the case for only 3 hours out of the 8760 hours in the year 2019.

The aFRR data is slightly modified to avoid infinite energy trading in the model. At some moments the aFRR-up prices are higher than the aFRR-down prices. That was the case for around 4500 to 6200 time steps out of the 35040 steps in a year simulation for 2016 to 2019. These data points are modified so that the price of the aFRR-up market was lowered to become equal to the aFRR-down rates. On average, the difference that had to be compensated for was only €4,20. So, it should not have significant effects on the results for the market.

In Figure 4.1 (next page) the sensitivity of the model to changing the electricity price data between the years 2016 to 2019 is shown. The difference between the most and least beneficial years is about 10%. 2018 tends to be the most successful year.

These differences can be explained by the varying levels of imbalance throughout the years. Yeas with higher imbalances have larger price spreads which are beneficial for the battery system. Also, the average prices on the markets potentially lead to severe variation in profitability between the years. In the simulations in this research, 2019 data is used unless stated otherwise. 2019 can be seen as an average year regarding the electricity prices, see Figure 4.1. These results are also reflected in the price data analysis in Appendix B. In the appendix, it can be seen that 2018 has the highest average prices. 2016 is the least profitable year. Moreover, in Appendix B it is shown that 2016 has a low standard deviation. A high standard deviation is the most valuable for the storage facility since it indicates larger price spreads which give rise to more electricity trading opportunities.

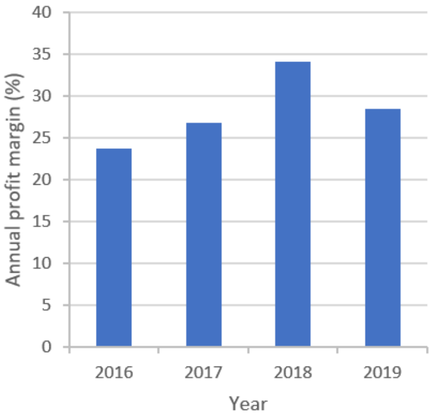


Figure 4.1: Profit margins of a flow battery with different price data.

Input for Monte Carlo method

The lastly required input for the technical optimization part of this research is for the Monte Carlo method. The randomized parameters are the battery energy capacity and its power capacity. These input parameters were randomly distributed between 50 and 1000 MWh for the battery volume and 10 and 700 MW for the power capacity. The Monte Carlo simulation was set to make 400 iterations.

4.1.2 Sensitivity analysis

The optimization model was run to research which technical characteristics and therewith which technology would be best suited for energy arbitrage purposes. Additional sensitivity analysis of the model can be found in Appendix C. From the sensitivity analysis it becomes clear that especially efficiency, CAPEX and cycle life play a significant role in determining the profitability of the battery system. OPEX and calendar life have less impact.

Furthermore, in this subsection, the behaviour of the model and the charging pattern of the battery model is analysed. Thereafter the sensitivity of the system to the capacity fading is assessed, which is of interest for the rest of the research.

4.1.3 Model behaviour

Validating a technical model can be done by actively controlling input parameters or variables, to be able to forecast the model's output. If the results are consistent with the hypothesis, without any significant deviations, the model can be considered valid.

The threshold of the optimization model is maximizing the revenues from trading electricity. To test the behaviour of the model three different analyses have been done with regards to the electricity price for single day simulations. If the trend in the price data is artificially fabricated, the response of the model's behaviour can be tested with extreme cases against expectations to validate it. First, if the market prices are kept constant throughout a full day, the hypothesis is that no trade will happen. No price incentive exists in trading electricity an hence the only expected behaviour is that the present energy at the beginning of the day will be sold and for the remainder of the day, no activity will occur. This is confirmed by running the model with constant and equal prices for the DAM and FRR market, see Figure 4.2.

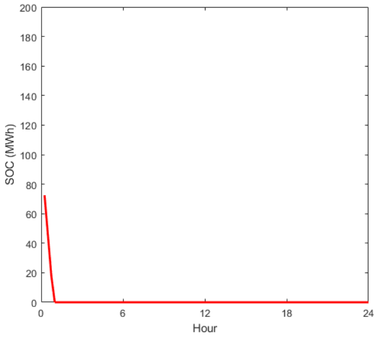


Figure 4.2: Charging pattern of one day of the BESF for a 200MWh/1110MW flow battery system with constant electricity prices.

Second, if the electricity prices would be decreasing with equal steps throughout the day, a similar pattern is expected. No price incentive will would be existing, so there would be no incentive to store any energy. The electricity present at the beginning of the day will be sold as fast as allowed by the ramp rate since the system is provided with the information that no better price incentive will be coming in the future. This is confirmed with the simulation, see Figure 4.3.

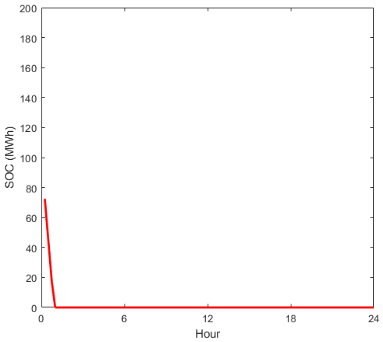


Figure 4.3: Charging pattern of one day of the BESF for a 200MWh/1110MW flow battery system with decreasing electricity prices.

Lastly, if the electricity price will keep on increasing with equal steps throughout the day, the hypothesis would be that electricity is bought as fast as possible and the battery system will remain at its maximum state of charge for the rest of the day. Also, this can be seen in the behaviour of the model, see Figure 4.4.

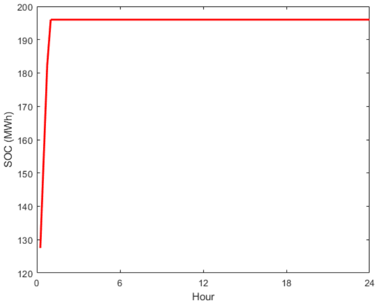


Figure 4.4: Charging pattern of one day of the BESF for a 200MWh/1110MW flow battery system with decreasing electricity prices.

Together these three analyses, validate the expected behaviour of the model since no deviations are observed and they hypotheses are confirmed.

Charging pattern

The optimization model resulted in a charging pattern of which a typical week can be seen in Figure 4.5, which shows the state of charge at every time step throughout the first week of January 2019. The input parameters of a 100 MWh/100MW flow battery was used to obtain the pattern. The figure clearly shows that the simulation is constrained by the maximum SOC of 98% of the total volume and the lower limit of the flow battery is 0%. Furthermore, it can be seen that the charging pattern is constraint by the maximum ramping rate determined by the C-rate as described in Equation 3.10. A 100 MWh/100MW, can be fully charged in one hour, so in four time steps of a quarter-hour. In the figure, one can observe that indeed the maximum ramping does not exceed 25% of the battery volume per time step.

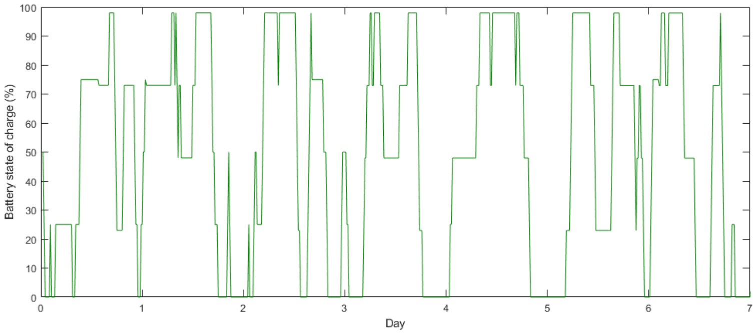


Figure 4.5: Charging pattern of the BESF with flow batteries.

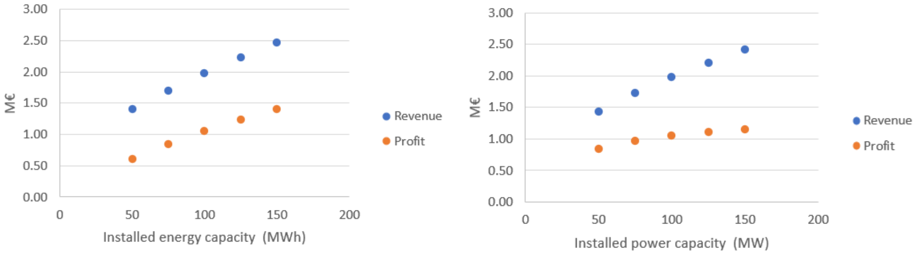
Moreover, the charging pattern of a week shows roughly 10 cycles. Over the whole simulated year, the battery goes through about 2500 cycles (6.75 per day on average). This indicates that 5% of the total cycle life of 50,000 cycles is used per year. This is in line with the constraint that the cycles are evenly distributed throughout the whole technical lifetime of the battery. The flow battery has a calendar life of 20 years. Therefore, it can be stated that in this simulation the calendar lifetime and ramp rate are the limiting factors for making more cycles.

Sensitivity of power capacity and energy volume

The systems profit is highly sensitive to the installations costs of the system. However, the revenues are not affected by the costs of the system, see Figure 4.6. This can be explained by the fact that the optimization threshold is maximizing the revenues from trading electricity. The costs of installation are not expected to influence that. From this result, it can be concluded that costs do not influence the behaviour of the system, only the resulting financial parameters that are required to determine the systems business case. Furthermore, in line with expectations, significant system costs (multiplied by ten) do not allow the battery system to become profitable.

Figure 4.6: Effect of increasing system costs for a 200MWh/110MW flow battery simulated for one week.

This effects can also be seen in Figure 4.7. It shows that increasing the system's size (both energy and power capacity) increases the revenues at a faster pace then it does for the profits.



(a) Effect of installed energy capacity on revenue and profit for a flow battery for one week of operation.

(b) Effect of installed power capacity on revenue and profit for a flow battery for one week of operation.

Figure 4.7: Effects of installed energy and power capacity for a flow battery.

Furthermore, Figure 4.7 confirms the linearity of the model. The output of the model (i.e. revenue and profit) should scale linearly with input. Increasing the installed energy or power capacity linearly increases the resulting revenues from trading electricity and hence the profits.

Sensitivity to capacity fade

The effect of the capacity fade on the maximal possible SOC of the battery is shown in Figure 4.8. The figure is based on the input parameters of the flow battery and a total 'end-of-life' capacity fade of 35% of the installed battery volume. Over one fully simulated year, the battery loses about 1% of its capacity due to cycling. It is very minimal because flow batteries have a high cycling life and therefore lose little capacity per cycle.

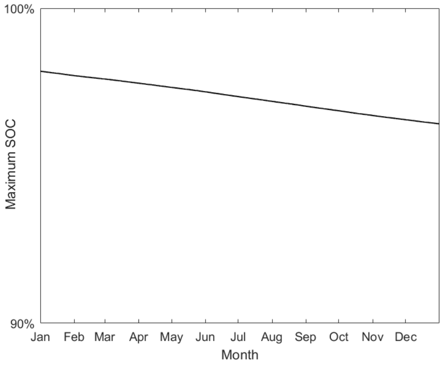
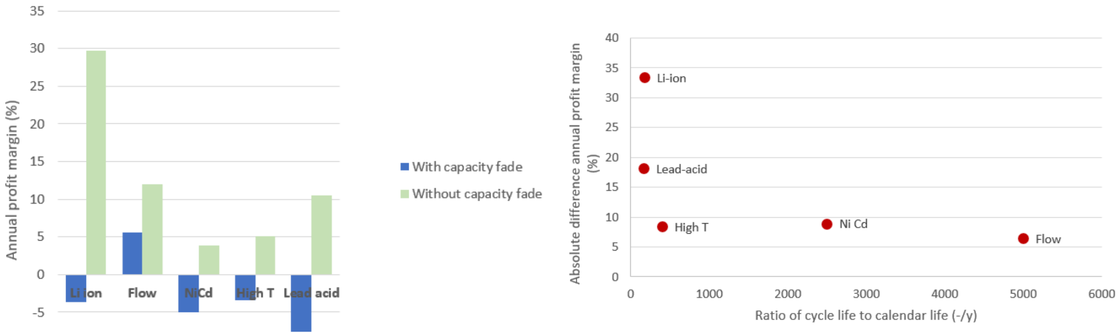


Figure 4.8: Effect of capacity fade on maximum reachable state of charge of a flow battery.

As mentioned before the capacity fading in this model is either determined by the calendar lifetime or on the cycling life of the considered battery system.

Since capacity fade will not be included in the MPC algorithm, the sensitivity of the profit has been analyzed in the optimization model. They are shown in Figure 4.9.



(a) Effect of capacity fade on annual profit margin .

(b) Absolute difference in profit margin between with and without capacity fade relative to cycling/calendar life time ratio.

Figure 4.9: Effects of capacity fade with 100MWh/100MW battery sizes.

The results show that for Lithium-ion and lead-acid batteries the difference in profitability is very big. There many factors that play a role in causing these difference. The major influence is from the technical lifetime of the batteries. It shows in Figure 4.9b the difference between with or without is mainly determined by the technical calendar life in combination with the cycle life of each technology. If the capacity fade is not taken into account, there is no limit in how much cycles are used within one year. Energy arbitrage builds upon trading as much energy as possible and makes use of as many price difference as possible. The model will therefore always use as many cycles as allowed within the constraints to make use of these price margins. The constraint that is left to be limiting when capacity fade is not considered is the ramping of the system. This can be seen in Figure 4.10. It shows the share of total cycle life which is used within the one year of operation. As can be seen, the Li-ion and Lead-acid batteries go through more than twice their total technical cycle lifetime if no capacity fade is assumed. The flow battery uses just 6% of its entire cycle life in the simulated year, which indicates it could run 16 years before replacement of the battery pack is needed. For the Lead-acid and Li-ion, it would mean that the battery pack has to be replaced twice a year. Since the battery pack is the most significant component of the capital expenditures (CAPEX) of the system [81], that would lead to a significant increase in actual costs. In summary, it can be noted that capacity fade can have significant effects on the profitability of a BESF. Later on in this research, a more thorough sensitivity analysis of the technical life with regards to cycling and calendar is shown in the next section, Section 4.1.5.

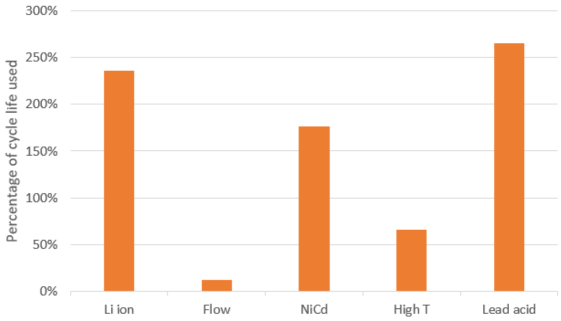


Figure 4.10: Percentage of cycles used of total cycle life without capacity fade. (100MWh/100MW).

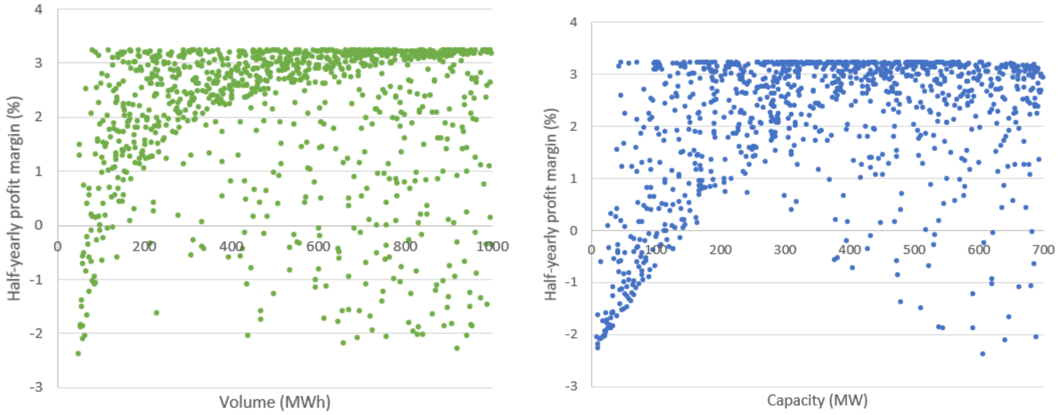
It is shown that flow batteries are the only technology that returns a positive result when capacity fade is considered. This can be explained by the relatively low costs of the system and long technical life. The flow battery also shows the least effects when it comes to in- or excluding the capacity fade.

4.1.4 Sensitivity minimal SOC

Earlier has been described that in this optimization model for the technical characteristics of the battery system the FCR market is not taken into account. It is stated, that for the technical optimization, the revenues from the FCR are not relevant yet. Furthermore, reserving capacity for the FCR market means that a certain share of the battery cannot be used. Therefore, in this phase reserving FCR capacity would have the same effects as increasing the minimal SOC. In Figure C.4b in Appendix C, the effects of increasing the minimal SOC on the annual profit margin are shown. As can be seen, if the lower limit of the state of charge is increased, this has very minimal effects on the annual profit margin. Therefore, it can be said that the exclusion of the FCR market in technical optimization has no significant impact on the results. In the next section, the simulation of the operation of the battery with the model predictive control, the FCR market will be included. There it will be shown what the impact on the profits will be to trade on the FCR market.

4.1.5 Monte Carlo simulation

With the Monte Carlo method, the effects of installed energy and power capacity have been researched. The results for varying the energy and power capacity are shown in Figure 4.11. It shows that in general the profit margins increase with increasing system size. It can be approached as a logarithmic relationship with the system size. Since higher power capacity allows for faster cycling of the system, it results in higher profit. Also, higher energy capacity allows for more energy to be sold or bought, so the margins between the electricity price can be used upon larger volumes of energy, resulting in higher profit.



(a) Half-yearly profit margin versus storage volume. **(b) Half-yearly profit margin versus the power capacity.**

Figure 4.11: Half-yearly profit margin relative to the flow battery's size and capacity. Results are from half-year simulations of 1000 Monte Carlo runs.

However, as can be seen, more negative results are observed above an installed capacity of 400 MW. Furthermore, if no saturation of the market would occur, this can be explained by the fact that the maximum number of cycles is reached. For example, if the capacity would be high, let say 600 MW, and the volume very small, let say 100 MWh, the trading behaviour is limited by the technical life of the battery. The C-rate would allow for very fast cycling, but lifetime limits are then the major constraints. The opposite holds for large volumes in combination with small capacities. In that case, the cycling pace is the limiting constraint.

It must be noted that the FRR market will this can be explained by the fact that the FRR market is limited in size and the market will be saturated at such high capacities. However, this limitation is not bounding the model and therefore this effect is not reflected in the results.

Besides, a clear upper limit in the profit margins is observed. The origin of this upper limit is also the maximum ability of trading of a battery system. This upper limit is reached at the optimal C-rate. Therefore, together, the results of Figure 4.11 are combined in Figure 4.12. When the installed power capacity is divided by the energy capacity, the C-rate is calculated. The C-rate determines how fast the battery can charge or discharge its full energy volume. Therefore, it also determines how fast the battery can go through its cycles.

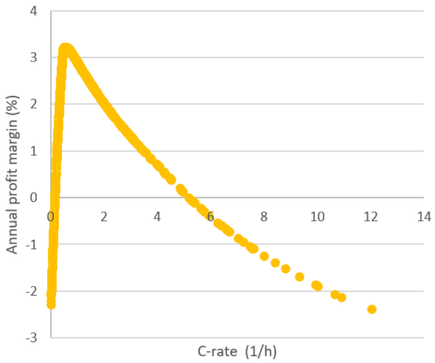


Figure 4.12: Half-yearly profit margin relative to the flow battery's size and capacity. Results are from half-year simulations with 1000 Monte Carlo simulations.

As can be seen, for the flow battery the ideal C-rate of 0.55 results in the highest profit margins. This indicates that if an array of 100 MWh is installed, the ideal power capacity would be 55 MW. Or with other words, this implies that the battery can be fully discharged in about 2 hours. In general, higher C-rates result in faster cycling, which is a beneficial characteristic of energy trading. However, faster cycling also leads to faster degradation of the battery. Therefore, an optimal trade-off can be found between these two characteristics. It is found that the C-rate appears where the total cycles per year allowed to fully fulfil the calendar life is optimal. Also, the costs of the system play a role in this trade-off. High power-based CAPEX, could result in the fact that installing a lower power capacity, and hence a lower C-rate, is more profitable. Vice versa holds for high energy based CAPEX. The sensitivity of the annual profit margin to the CAPEX is shown in Appendix C.

The optimal C-rates for the five different battery technologies are shown in Figure 4.13 (next page). The optima are found with 400 runs of half a year with the Monte Carlo simulation.

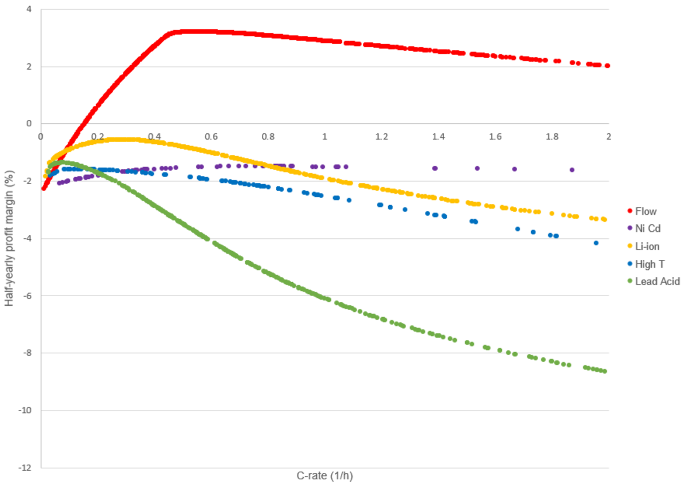
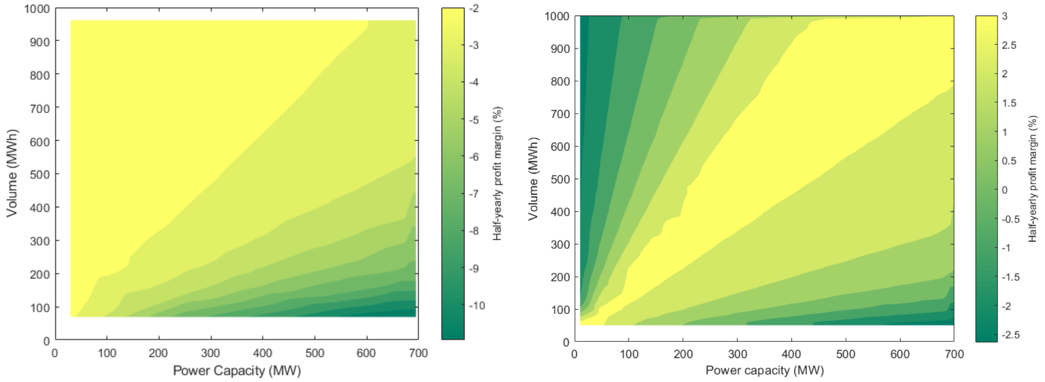


Figure 4.13: Half-yearly profit margin versus the C-rate.

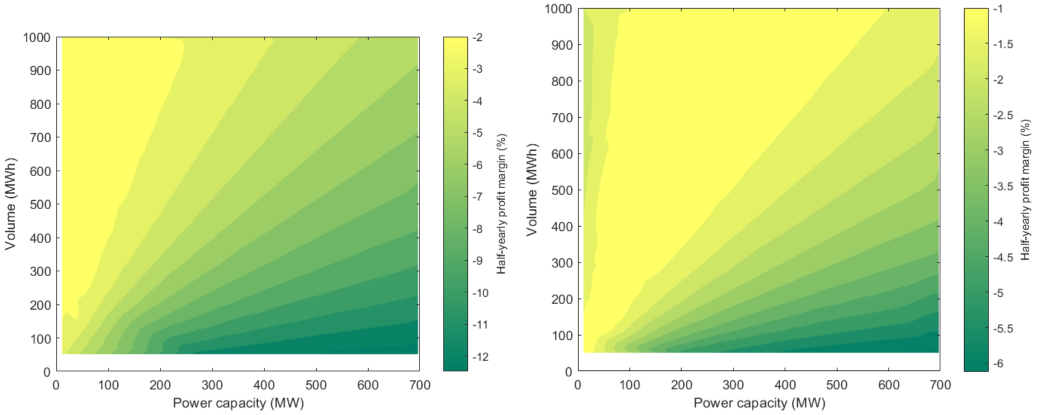
The lead-acid battery shows the worst results. This can be declared by the fact that they have low technical lifetimes (calendar and cycle life) an very high power based CAPEX. The high costs of the high-temperature NaS and nickel-cadmium batteries are also reflected in the graph. It shows that have lower cycle life, high calendar life and higher costs result therefore in being the least profitable options. As shown, all technologies return negative profit margins, except the flow battery. They are not able to cover the costs of the system with pure energy arbitrage and therefore result in negative profit margins. The flow battery, on the other hand, reaches more than 3% of half-yearly profit margins and comes out as the optimal technology based on the presented optimization model.

The data is also shown in the following surface plots for each technology individually, see Figure 4.14 (next page). It shows the linearity of the optimization model, but also how the various technologies show different sensitivities to the installed power and energy capacities. For example, the high-temperature battery is more profitable with low power capacities and high energy volumes due to the significant power capacity based CAPEX of the technology, while the flow battery shows more resiliency towards the power capacity. For more detail, in Appendix C the sensitivity of the model towards the energy and power-based capacity is shown.

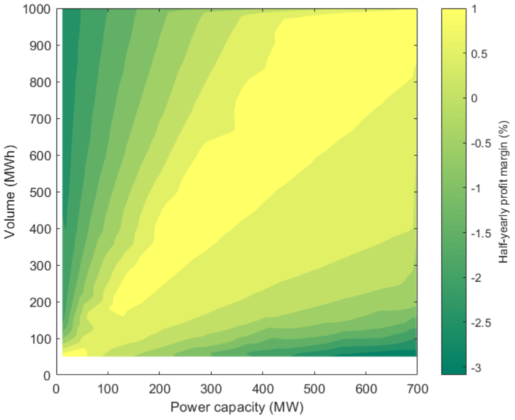
The optimal results for all the five battery technologies extracted from the above-presented data from the Monte Carlo method are shown in Table 4.2 (page 63). The best C-rates and their accompanying optimal profit margins are listed.



(a) High T. **(b) Flow.**



(c) Lead Acid. **(d) Li-ion.**



(e) Ni Cd.

Figure 4.14: Half-yearly profit margin relative to the installed power capacity and volume per technology. Results are from half-year simulations with 400 Monte Carlo simulations.

Table 4.2: Best C-rate per technology.

	Best C-rate (1/h)	Maximum half-yearly profit margin
Flow	0.55	3.22%
Li-ion	0.29	-0.55%
High T	0.13	-1.58%
Ni-Cd	0.80	-1.49%
Lead Acid	0.08	-1.35%

Sensitivity to technical lifetime

A Monte Carlo simulation of 150 runs has also been executed for the sensitivity of the profit margin to the calendar life and cycling lifetime of the optimization model. The battery used in the simulation is the flow battery. The results are shown in Figure 4.15.

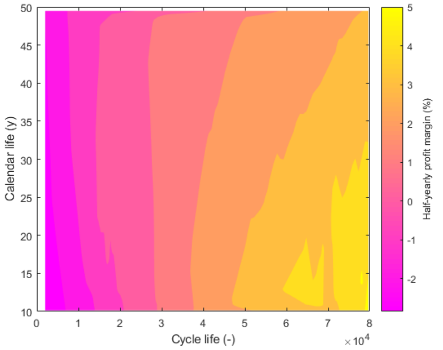


Figure 4.15: Surface plot of sensitivity of profit margin to technical lifetime for a flow battery. Results are from half-year simulations with 150 Monte Carlo simulations.

It confirms the fact that longer calendar lifetimes result in a lower number of cycles allowed per year and hence lower annual profit margins. Therefore, short calendar lifetimes and high cycle lifetimes return the highest profit margins. Besides, higher profit margins result in shorter pay-back periods. Nonetheless, it must be noted, that shorter calendar life directly results in the fact that the battery pack needs to be more regularly replaced. This will significantly increase the CAPEX of the system [81]. So, a trade-off has to be made between high annual profit margins with batteries with a short technical life versus a battery system, with lower profit margins, but longer lifetimes.

Also, the sensitivity can be confirmed by results from other research that also have shown that calendar life has a more significant effect on the degradation of the battery than cycle life [85].

4.1.6 2030 scenario

It is often mentioned in research that the costs of battery technologies are decreasing at a fast pace. Therefore, it can be interesting to see what the effects on the profitability will be in the future. The International Renewable Energy Agency (IRENA) has sketched a scenario for 2030 for many battery characteristics for the Li-ion, high temperature, Lead-acid and flow batteries [10]. The average outcomes of their 2030 estimations are shown in Table 4.3.

Table 4.3: 2030 scenario for battery characteristics from IRENA [10].

	CAPEX (€/kWh)	Cycle life	Calendar life (y)	Minimal SOC (%)	Efficiency (%)
Li-ion (NMC)	185	5000	20	10	96
High T (NaS)	200	10,000	25	0	85
Lead-acid	135	3500	15	20	85
Flow	205	50,000	20	0	80

All energy based CAPEX are likely to decrease on average with 55% compared to the data from nowadays from Table 4.1. Therefore, it can be assumed that it will not have any significant influence on what technology comes out as being most profitable in the presented technical optimization model.

For the absolute profitability, the 55% price reduction has significant effects. For a 200MWh/110MW flow battery, the annual profit margin is likely to increase, with a profit increase of 18.8 M€, to 16.1% in 2030 compared to 6.1% in present-day. Note that all other technical parameters, which are not mentioned in Table 4.3 are assumed to be equal in 2030 to the present-day simulation. This shows that reduction of the capital costs wit 55% has an even bigger effect on the profitability. Eventually, leading in 2030 to more than 2.5 times the estimated profitability of today.

4.1.7 Summary

In summary, the results of the technical optimization model show that high calendar lifetimes in combination with cycle life (and therewith also capacity fade) are considered to be the most important parameters regarding the sensitivity of the profitability of a battery system for energy arbitrage purposes. Both parameters allow for more cycling within a certain period and hence allow for more revenues from trading electricity.

The flow battery shows the most promising results, reaching an annual profit margin of 5.61% at the optimal C-rate of 0.55 per hour. In addition, the flow battery shows the least significant response upon elimination of the capacity fade. Lastly, looking at the future towards 2030, this battery technology is shown to be very promising. Therefore, this technology is further assessed in the model predictive control simulation.

Based on this optimization model for the technical characteristics of the battery system, subject to the assumptions, perfect foresight and optimal estimation of parameters, it can be said that flow batteries could provide a financial incentive to be installed. All other technologies do not show positive results.

4.2 Simulation

This section represents the result of the simulation of a flow battery with a model predictive control (MPC) algorithm. It starts with information on the used input data, then the sensitivity of the algorithm to different price scenario's is presented. Thirdly, the activity of the battery system on the various electricity markets is described and lastly, the sensitivity of simulating only one year of operation is given.

4.2.1 Input data

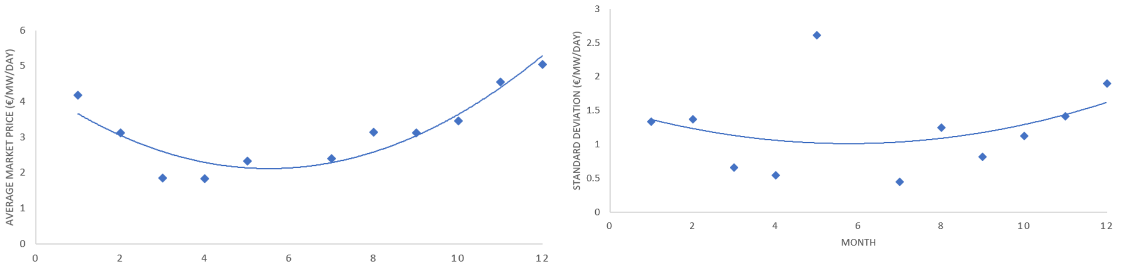
In the technical optimization of the utility-scale battery energy storage facility for energy arbitrage purposes it was found that the flow battery had the most promising technical characteristics. Therefore, the flow battery is used as a basis for the MPC algorithm.

Furthermore, as mentioned in the methodology, a few extra input parameter have to be defined in the MPC algorithm. Starting with the forecast horizon. For the DAM a forecast horizon of 2.5 days is assumed. Since the bids are optimized at half a day in advance, the forecast horizon had to be at least 1.5 days. For the FRR market, a forecast horizon of 6 hours is obtained. The latter market is hard to predict and therefore has a short forecast horizon.

Market price data

In the MPC simulation model, the same price series are used for the optimization model of Section 3.1. So, price data of 2019 is used for the FRR market and DAM since that year is an 'average' year regarding the electricity prices compared to the years 2016 to 2019. The forecast price data is generated with Excel. There are three sets of forecast data generated. The first set, called the 'perfect forecast' is the same as the real electricity data. Second, the 'good forecast', is generated by taking a random number between previous and next price data point of the actual data. The 'medium forecast' set is created similarly, but taking a random number between the past and following three data points. It must be noted that this is not an accurate or realistic manner to forecast electricity prices. Still, the forecast price series are only to test the operational tool. In 'real-life' more precise and realistic price forecast could be used. It is assumed here that the participation of the storage facility does not influence the market prices.

Furthermore, a new price series was needed to implement the FCR market in the simulation model. In this market, some changes have occurred recently (as discussed in Section 2.3.5). Therefore, the daily FCR data of 2019 was only available from July 2019 onwards. To be able to simulate a whole year, the data points for the 1st of January to the 3rd of June were taken from 2020. For the remaining data points in June, the pattern of average market prices per month, as well as the standard deviation per month, has been taken into account. The patterns are shown in Figure 4.16 (next page). Based on the parabolic patterns, a standard deviation and average are determined for June. The missing data points in June were then randomly generated with a normal distribution based on the for June estimated standard deviation (1.0117 €/MW/d) and average (2.1314 €/MW/d).



(a) Monthly average with parabolic trend line.

(b) Monthly standard deviation with parabolic trend line.

Figure 4.16: Monthly average and standard deviation of the FCR market prices for 2019.

4.2.2 Model behaviour for different price scenarios

The MPC model requires a forecast electricity price series. On this series, the optimized trading schedule will be based. To validate the behaviour of the model, three different price scenarios were defined and results are compared to the optimization model without MPC. This sensitivity analysis hypothesises that a more accurate forecast leads to higher profit margins. The used scenarios were defined as follows; the 'Perfect Forecast', 'Good Forecast' and 'Medium Forecast'. If every price data point is compared to the real electricity data, an absolute difference can be calculated. The average percentage difference in each scenario compared to actual data is shown in Table 4.4. Since the 'Perfect Forecast' is the same as the real data, results from this simulation will represent the maximum reachable profit margin. The 'Good' and 'Medium' scenarios have an increased forecast error.

Table 4.4: Average percentage difference compared to real price for the price forecast scenarios.

	Medium Forecast	Good Forecast	Perfect Forecast
DAM	9%	4%	0%
FRR up	61%	33%	0%
FRR down	72%	49%	0%

The effects of these forecast errors in on the annual profit margin of a 100MWh/100MW flow battery simulated with the MPC model are shown in Figure 4.17 (next page). Note that in this simulation the cycling life of the flow battery was 100,000 cycles. That is too high and therefore, the absolute numbers are not an indicator for the actual annual profit margin. Nonetheless, the figure can be accurately used to compare the different price forecast scenarios. As can be seen, the maximum reachable profit with the linear optimization model was around 12% of the capital investment. However, that was based on known electricity prices for a full year. Since the MPC can only look ahead up to a predefined forecast horizon, less optimal results will follow. The effect of this shortened forecast horizon is already a decrease in the annual profit margin of about 50%. Then taking into account forecast errors with the 'Good Forecast' and 'Medium Forecast' electricity price scenarios, it can be seen that the profits reduce even further. For the 'Medium Forecast' price scenario, this even led to negative results, which indicate that the capital and operational expenditures cannot be covered with energy arbitrage. Moreover, these results are similar to the hypothesis that more accurate price forecasts lead to higher profit margins and therefore validates the model.

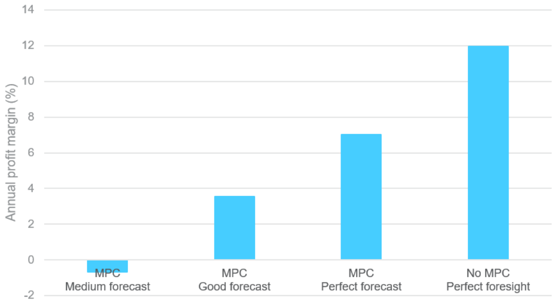


Figure 4.17: Annual profit margin for a 100MWh/100MW flow battery with different price forecast scenarios.

With these results, it can be said that adequately forecasting electricity prices result in higher profits and also in better revenue forecasting, which is crucial in determining a business case.

4.2.3 Comparing the markets

Comparing the share of traded energy volumes at each market result is the data with the 'Perfect Forecast' scenario, shown in Table 4.5. As can be seen, most of the electricity is traded on the FRR market. Note that even buying on FRR results in positive revenues stream over the whole year caused by negative electricity prices.

Table 4.5: Share of traded energy at each market with MPC and perfect forecast scenario. Input is a 100MWh/100MW flow battery and 25% of energy capacity reserved for the FCR market.

	Share in total profit	Share in total revenue	Share in total electricity expense
DAM	-3%	0.43%	100%
FRR	102%	98.97%	-
FCR	1%	0.61%	-

The electricity trade on the DAM is even negligibly small. This can be explained by the fact that the price spread on this market is very small compared to the FRR market. This indicates the price volatility has a very significant effect on the profitability of the battery system. Furthermore, the DAM is only sometimes addressed to sell electricity and seldom to purchase. Electricity prices on the FRR-down market are lower on average than the DAM, resulting in a choice to buy on the FRR market rather than the DAM.

Also, the FCR revenues are minimal compared to the FRR market. It could indicate that it might be more profitable to exclude these market from the model and solely focus on the secondary control market in the Netherlands. That also has the potential to leave room for stacking revenues by setting the battery facility in for other use cases. Similar results are obtained if the MPC simulation is executed with only the individual markets, see Table 4.6.

Table 4.6: Results based on individual markets simulated with MPC and perfect forecast scenario. Input is a 100MWh/100MW flow battery and 25% of energy capacity reserved for the FCR market.

	DAM	FRR	FCR
Income from sold electricity (k€)	3.4	18,503.7	112.5
Income relative to OPEX and CAPEX	0.03%	168.7%	1.03
Total profit (M€)	-11.1	+9.8	-10.8
Annual profit margin (%)	-8.5%	7.5%	-8.3%

The small contributions of the FCR market for the 'Medium Forecast' scenario of the flow battery are also shown in Figure 4.18. The results show that increasing the contracted FCR capacity leads to an increase in profit margin, although very minimal. This capacity is, however, bound by the rated capacity of the BESF. Therefore, it will never contribute very significant portions to the revenues compared to electricity traded on the FRR market. Furthermore, since the average contracted capacity of the FCR market is not higher than 45 MW per day ([33]), it is not realistic to offer this full capacity on the market. If the full capacity would be offered by only one party, price incentives will disappear due to the lack of competition. Therefore, contributions of the FCR to the total revenue will remain very small on utility-scale battery energy storage.

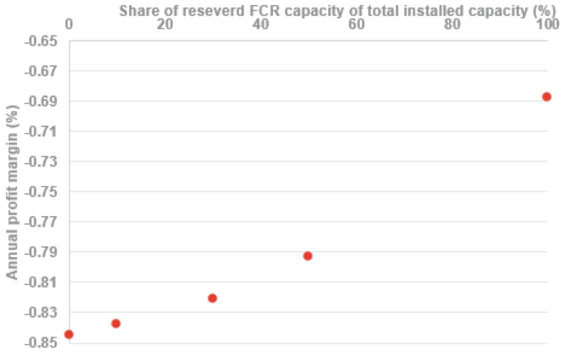


Figure 4.18: Annual profit margin for a flow battery versus the reserved FCR capacity with MPC.

This market 'cannibalism' is a much smaller concern for the FRR market. On average in 2019, the accepted power was about 400 MW on the FRR-up market and about 800 MW on the FRR-down market. The analyses in this research are limited by about 200 MW (except in the Monte Carlo simulations), so the effects on the market prices of the FRR markets by the participation of the BESF are smaller. Nonetheless, they are not negligibly small, the participation on the market might, therefore, result in lower price spreads and hence lower price incentives for the storage facility.

4.2.4 Multiple years of operation

The model simulates just a single year of operation, while in reality, the battery system will be operating for its full technical life. Therefore, a comparison is made between the annual profit margin of the first and last year of the technical life of the battery. The following figure shows the difference in annual profit margin for a 200MWh/110MW flow battery operated in the first and last year, see Figure 4.19.

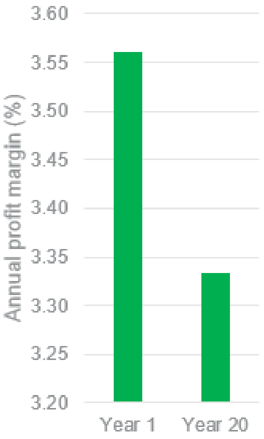


Figure 4.19: Annual profit margin for the first and last year of operation with perfect forecast scenario. Input is a 200MWh/110MW flow battery.

As earlier shown in the sensitivity analysis of the optimization model, the model is not very sensitive to changing the SOC limits, see 4.1.4. Since the capacity loss influences the maximum state of charge, this has no severe effects for the profit margin. The figure above shows that for the last year of the technical lifetime, when the capacity fade at the start is already slightly over 60 MWh (30%) of lost energy capacity, the annual profit margin only decreases with 6% from 3.56% to 3.33%.

So, it can be said that the results validate that the single simulated year in this research is a good indication for the operation of the battery system throughout its whole technical life because the state of charge limits have little influence on the annual profit margin.

4.2.5 Summary

Based on the above-presented results of the optimized operation of a battery system with a model predictive control algorithm, it can be said that the profitability of a flow battery is highly sensitive to the accuracy of the price forecast. Furthermore, the most important market for the battery system is the automatic frequency restoration reserve. The day-ahead and frequency containment reserve lead tot only slight contributions in the profitability.

Furthermore, based on the results of the MPC model, it can be said that under the presented conditions and restrictions a flow battery of 200MWh/110MW has potential to be profitable under profitable in at least 'Good' price forecast scenario. However, it must be noted that the most ideal battery characteristics were taken into account, which could lead to an overestimation of the profitability.

Lastly, it can be said that the MPC model, with the linear optimization algorithm as the basis, shows results in agreement with the expected and desired behaviour of the model and can, therefore, be validated as an effective way to simulate optimized electricity trade for a BESF in the Netherlands. However, more accurate price approximations and system costs reductions would be needed to return better results for a suitable business case. The Perfect and Good forecast scenarios show that, under the considered assumptions, an increase in forecast accuracy can provide significant contributions to the profitability of the system.

4.3 Financial results

The above-described results of the technical optimization and the operation simulation are based on simple profit calculations. In this section, the costs of financing are included and the results are presented to give a more realistic indication of the reachable profits of a flow battery operated with the model predictive control method. First, the input data for the economic assessment is presented, then the effects of varying the interest rates and lastly the resulting LCOS of the model are compared to LCOS found in the literature.

4.3.1 Input data

The most optimal C-rate of the flow battery was found to be 0.55 per hour and therefore this will be used in the financial analysis. The size of the system is set at 200MWh/110MW. The CAPEX and annual OPEX of the flow battery are shown in Table 4.1. Furthermore, the results of the 'Perfect Forecast' scenario of the MPC algorithm are used.

To calculate the cost of financing for the battery facility, some assumptions have to be made. The debt share of the investment is set at 50%, the annual interest rate on the debt is defined at 6%, the debt term is determined to be equal to the technical life of the battery and an 8% cost of equity is assumed. Furthermore, the corporate tax in the Netherlands is 25%. [82, 56].

4.3.2 Profit and payback-period

The preliminary calculation of the annual profit margin based on the above-described flow battery operation with MPC was calculated to be 3.33% in the perfect forecast scenario. This was the result of a profit of 6.62 M€, a total CAPEX of 198.7 M€ and OPEX of 4.9 M€/y. It would mean that it should take the facility 30 years to earn back its investment and get to a break-even point. Note that the technical calendar lifetime was only 20 years. Therefore, the investment will not be earned back before the battery is at the end of its technical life. If a break-even point should be reached within at least 20 year, the profits should increase with 3.3 M€ to 9.9 M€. Note that this would only cover for the CAPEX and not the OPEX. That would require a significant increase in revenues to overcome the high system costs. Increasing the revenues could be realized with technical and cost improvements of the battery technologies, larger price spreads on the electricity markets with accurate price forecasting methods or lastly, by stacking revenues with other use-cases in addition to the energy arbitrage.

This calculated profit, does not even include costs of capital. The calculation of annual costs of financing, based on the above described financial parameters is shown below:

$$\begin{aligned} Yearly\ cost\ of\ financing &= \frac{r}{1-(1+r)^{-LT}} * CAPEX * Debt\ share \\ &= \frac{0.06}{1-(1+0.06)^{-20}} * 198.7 * 50\% \\ &= 8.7M€ \end{aligned} \tag{4.1}$$

If this cost is taken into account, it leads to an actual annual profit of -2.08 M€ and hence profit margin of -1%. Instead of increasing the revenues with 3.3 M€ as mentioned above, this would require an increase of about 12 M€ for the perfect forecast scenario. Therefore, it can be said that the battery system from this research is not profitable based on optimized operation with a model predictive control method if half of the investment is done with external funds.

In the 2030 scenario, with an energy-based CAPEX cost reduction of 55%, the results of the MPC operation were a profit of 14.6 M€ and an annual profit margin of 10.0%. The total CAPEX are in the 2030 scenario 79.6 M€ and the OPEX remain the same as present-day. The new costs of finance would be 3.5 M€ annually. So, if these were taken into account, which are significantly lower since the CAPEX are smaller, the profit would be 8.1 M€ with an annual profit margin of 10.1 %. This would mean that the investment costs would be earned back after 10 years, which is half of the technical life of the flow battery. Therefore, in 2030 the battery system has the potential to be profitable if operated for energy arbitrage purposes only.

4.3.3 Sensitivity for interest rate

In the costs of financing calculation, quite some assumptions are made. Especially when looking at 2030 there is no security that the interest rate on debts remains constant. Therefore, in Figure 4.20 (next page) the sensitivity of the cost of financing is shown.

It shows, that the interest rate can have a significant impact on the profitability of the battery system. From an interest rate of 2.7% or lower, the system starts to return positive profit margins.

4.3.4 LCOS

As can be seen in the comparison of first and last year of operation, little effects are noted at the end of life versus the beginning, therefore it can be assumed that the revenues are constant over the whole technical life.

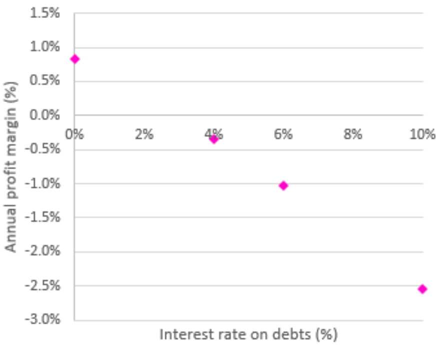


Figure 4.20: Annual profit margin sensitivity to interest rate for a 200MWh/110MW flow battery.

The levelised cost of storage (LCOS) that result from the MPC simulation of a 200MWh/110MW flow battery in the 'Perfect Forecast' scenario was found to be 428.81 €/MWh. This is based on a discount rate of 6% which was calculated with according presented input data of this section and to Equation 3.30. The interest rate is assumed to be at the same as the WACC.

Typical LCOS for flow batteries found in the literature are of a system at utility-scale are between 228 and 440 €/MWh [8, 81]. These values of LCOS found in the literature found were based on an interest rate of 8%. If the LCOS of this research is based on an interest rate of 8% an LCOS of 437 €/MWh follows, which is on the higher end of the range found in the literature. Furthermore, the costs data used in this research is optimistic, therefore the, in reality, the LCOS can become even higher. Although, these CAPEX used are in the same order of size as the assessed research of comparison [81]. Therefore, it does indicate that the presented model is valid compared to other research to be used to identify the ideal configuration of a battery energy storage facility and to simulate optimized operation with an MPC method since there is no significant deviation. Note that this does not indicate that the presented LCOS can also be reached in reality due to the limitations and constraints of this research.

5 | Reflection and Future Research

This chapter discusses the major assumptions and limitations that have not been discussed in Chapter 3 and 4. Furthermore, further implications that can be drawn from the results are presented and a reflection is provided. Lastly, recommendations for future research are provided.

5.1 Reflection

5.1.1 Optimization model limitations

Firstly, due to the linearity of the model, simultaneous charging and discharging of the battery is possible. As a result, it is possible that for example in one time step electricity is bought on the DAM and directly sold on the FRR market. The model could be broadened to prevent this from happening. However, the effects of this phenomena have been proven to be negligibly small [82]. This is also shown in the results chapter, Chapter 4. Most electricity is traded on the FRR market and the share of trade on the DAM is not significant. This confirms the negligibility of these effects.

Secondly, in the presented model, the upper and lower state of charge limits were 'hard' limits to reduce computation time. Although in reality, it could be decided to surpass these limits if the price benefit is significantly large and therefore could overcome the battery degradation costs caused by crossing the limits. In future research, the SOC limits can be approached as 'soft' limits [73, 67]. Implementing the soft limits requires a more sophisticated optimization model that will require longer computational times. Nonetheless, to ensure the stability and suitability of the battery system it is been said that it is necessary to keep the hard SOC constraints in the design phase[67].

Thirdly, assumptions with regards to the cost modelling of the battery systems. The costs of the system are assumed to be linear over the technical life and to scale linearly with system size. When designing a real business case, this would not be sufficient to identify the risks and opportunities. A more thorough system price study would then be necessary. However, for this research, intending to find the optimized system configuration and operation, a more elaborate price study was not essential.

Lastly, in Subsection 4.1.5, it is noted that longer calendar lifetimes result in a lower number of cycles allowed per year and hence 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 pay-back periods. Nonetheless, it must be noted, that shorter calendar life directly results in the fact that the battery pack needs to be more regularly replaced. This will significantly increase the CAPEX of the system [81]. So, 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. This trade-off has to be assessed to be able to come closer to solid investment analysis. It can be realised by internalizing the costs of re-powering the assets in the costs of the system.

5.1.2 MPC limitations and reflections

A lot of research has been done to identify the economic viability of energy storage. It has widely been shown that there exists a financial potential. Although, operational strategies are less commonly discussed. The used models in this research have been proposed by [74] and [28] to design a strategy for real-time and day-ahead electricity arbitrage. Those papers showed that MPC can reduce costs for storage in combination with VRES plants. This research is an addition to those papers by investigating the opportunities for independent storage. The independency and novelty result in a lack of a reference scenario to which the results can be compared. Nonetheless, the research shows how an MPC algorithm can be implemented to optimally operate a battery system for energy arbitrage. It shows that system costs, price spreads and forecast accuracy has significant impacts on the profitability of the system. However, this research is limited by the lack of comparison to other optimizing simulation methods or reference scenarios. Although it shows that the algorithm can effectively be used for the stated purposes, it could be possible that other methods provide even better simulations. Improvements in comparison to the MPC could be shorter computational times, less dependency on forecast accuracy or a non-linear basis for optimization.

5.1.3 Electricity price forecasting reflection

The results from this research indicate that the profits realized in the 'Good' scenario are only a third of the optimal and maximal profits resulting from the initial optimization model. Better price forecasts could, therefore, increase this with a perfect forecast up to 50% of the optimal profits. In line with [74, 86] and [28], the results, therefore, show that an adequate price forecast is very essential in realizing a potential business case. Nonetheless, the current electricity price forecast method used is completely at random and uses no sophisticated methodology. A thorough electricity price forecast study was outside of the scope of this research since the focus was on testing the operational MPC model. In reality, electricity prices are influenced by the many different market characteristics, nonstrategic or stochastic uncertainties, behaviour of the consumer and effects of time, season or year [87]. In future research, therefore, more attention can be paid to provide a realistic price forecast series to the MPC algorithm and to implement these effects in the trading strategy. Challenges to accurately do this would be the volatility of the spot and imbalance market prices. With better computational tools, better forecasts can likely be made.

Also, the present research is based on historical price data. Since the research was intended to test the specific simulation method, the result cannot be directly implemented to the specific investment risks. The use of historical price data explicitly excludes any effects that the storage facility itself can have on the market. Furthermore, the future promising effects of a growing share of intermittent renewable energy sources on the market prices are not included. Increasing shares of VRES are estimated to have a positive effect on the business case, so this should not lead to over-estimations. As mentioned before, future price data is hard to predict especially with the growing shares of VRES [88].

Moreover, it has been shown in this research that increasing the price spreads, results in higher profit margins for the BESF. Figure 4.1 shows that the price data of 2018, which were more volatile (the standard deviation of the data was 30% higher on average compared to 2019 data) lead to higher profits for the battery facility. Therefore, if even more volatility will develop in the future, this can lead to even higher profits. It must be noted, however, that in general more volatility of the electricity prices also leads to bigger forecast errors which can limit the financial opportunities of the increased price spreads. Also, if market prices become too volatile and therefore danger the security of supply, the market operator might cap the prices or changes the market structure.

The same holds for simulating the effect which storage itself has on the market prices. These effects might be minimal if no saturation of the electricity storage market occurs, but could become very big. This effect is called 'cannibalism' of the storage market value. It has been estimated that for one GW of pure storage, the arbitrage value on the market can reduce with 10% [89]. However, based on basic and natural market mechanisms, it can be said that market participation will stop increasing if profitability is not ensured due to the lower price spikes. In this research, it is assumed that the assessed storage capacities are not significant enough to influence the market price. Future research could go into more depth on the impact of large amounts of storage on the electricity prices and hence the value of the potential of energy arbitrage.

Improving the price forecast method could furthermore include weather dependencies, market price transition probabilities or advanced methods like machine learning. Also, any forecast changes regarding the Dutch market structure should be taken into account to make adequate price forecasts.

5.1.4 Summary

Summarizing, the strongest points of this research are the robustness and strong sensitivity analysis of the model. That enables future researchers to continue improving the models and makes it applicable for varying purposes. Also, the elaboration of the economic assessment, compared to previous research makes the possibility of building a real business case bigger. Weaker points are on the other hand the possibility of applying the exact resulting values to identify a real business case. The many assumptions and limitations, still refrain the outcomes to be directly used in a real-life business case analysis. The electricity price forecasts and battery costs model play major limiting roles. Furthermore, the objective function of maximizing the revenues from trading electricity makes the system very sensitive to the electricity price forecast which is undesirable. Potentially stacking revenues, or market reforms could reduce this dependency. Lastly, the lack of comparison of the MPC model to other simulation methods or reference scenarios limits the strength of the validation.

5.2 Possible improvements and future research

5.2.1 Stacking revenues

As mentioned before, most battery storage business cases make use of stacking revenues. It has been shown that a combination of the various use-cases and services in the Netherlands leads to the most profitable storage facility. Furthermore, combining the use-cases could also combine different risk exposures for batteries [45, 36]. Proving a single service with an energy storage facility makes is very hard to overcome the high capital costs [27, 44, 46].

Nonetheless, this research focused on the profitability of operating with the single use-case of energy arbitrage. Arbitrage opportunities entirely depend on the price spreads in the electricity prices. Since the financial analysis showed that the facility becomes non-profitable with already the 'Perfect Forecast' scenario, future research could be to look for possibilities of having extra revenue streams by providing other services. Revenues from other ancillary services or other use cases could be very economically attractive if they can provide a secure revenue [39].

A difficulty, however, arises when assessing other use cases to stack the revenues, since in many electricity systems no clear remuneration regulation exists. In a lot of countries, market regulations and structures will have to change to be able to create revenue streams for service providers. This is also the case in the Netherlands. The country should develop tools to transparently and robustly define financial incentives for providing services like congestion relief for the grid and time shift in (peak) demand [10].

5.2.2 Capacity markets

Following up the above subsection, capacity markets, like the Frequency Containment Reserve in the Netherlands, can provide the battery facility with such a base revenue. Capacity markets offer auction-based remuneration for providing sufficient energy generation capacity for periods of peak demand [10]. This market is relatively little assessed in this research while a capacity market has a lot of potential to be very beneficial for battery energy storage. Neighbouring countries like the UK and France already trade significant amounts of electricity on capacity markets. In the UK and Australia, successful commercially competitive projects have emerged on the capacity auctions [10]. However, in the Netherlands, there are no plans yet to follow their example to extend this. The only capacity market remains the FCR market, which offers just relatively small opportunities due to its limited size. In the current method of providing the reserved capacity for the FCR market, the offered power capacity of a storage facility must always be available, even if it is not necessary. Therefore, improved market mechanisms that offer long-term contracts could be designed to reduce the risks of investing [8]. This however still needs to be researched, since a lot of uncertainty still exists in determining the right level of financial incentive which is appropriate for energy storage facilities that offer reserved capacity [79].

Moreover, when batteries are installed, their rated power capacity limits the possibilities to participate in such a market. Higher power capacities could result in higher revenues from the FCR market, however, they also lead to higher installation costs. In this research, it has been shown (in Figure 4.18) increasing the participation in the FCR market directly led to higher profit margins since it was assumed that all offered capacity was accepted. In reality, this is not the case and leaves extra uncertainty.

5.2.3 Physical boundaries

Next, the boundaries in this report are set by the Dutch country borders. Trade of electricity is only considered to happen within the borders. Nonetheless, the Dutch electricity grid is highly interconnected with neighbouring countries. That might be needed to take into account to simulate the system closer to reality. The interconnection capacity could offer extra trading opportunities but also flattens price spreads on the markets.

Lastly, connection cable costs are not included in this model (only network usage tariffs). In this research, it is assumed that the cable is big enough for the system and would not be limiting. However, designing the system with the cable capacity as an optimization variable would elaborate on the model to be able to use it for real business case assessments.

5.2.4 Optimization objective

The decision threshold in the presented model of this research is to maximize the revenues from electricity trade. Therefore, the system will always trade electricity if it delivers any revenues. In other words, it will try to make use of any price difference present in the market as long as the not constraint by technical limits. The model will therefore always use as many cycles as possible within the constraints to make use of the price margins. That is because the energy arbitrage business case builds upon trading as much energy as possible. This results in the fact that the presented model does not take into the costs that are associated with cycling. This potentially leads to an overestimation of the profits. In further research towards building a solid business case for energy storage, among others, the costs of battery degradation and re-powering of assets should be internalised in the system [85].

This internalisation would 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 should be accounted for. The technical lifetime of a flow battery is 20 years and 50,000 cycles. Therefore, it could be said that a minimal price difference between the buying and selling price of electricity per cycle could be determined that would be able to cover these marginal costs. A potential trading strategy could, therefore, be to simulate the BESF with the constraint that only energy can be traded if the price difference is higher than this marginal costs.

5.2.5 Summary

Combining the above mention improvements, the research can be elaborated to further identify the validity of the simulation model. Several improvements can be done to experimentally researched the proposed methods. In this research, there is quite a high level of uncertainty due to assumptions made for simplification reasons. Therefore, the presented results can be best interpreted to be relative to each other, rather than absolute. Absolute values for profits that can be used to assess the business case of a BESF correctly would require a higher level of accuracy for the investors.

Nonetheless, the results of this research do indicate how well the algorithm works and how different technologies compare to each other.

6 | Conclusion

The current power system of the Netherlands is changing, VRES are quickly gaining shares in the electricity mix. It results in a need for more flexibility of the grid to be able to match supply and demand continually. Energy storage, and to be more specific, battery energy storage is a proven promising technology that can help to create more flexibility for the system. By storing electrical energy by converting it to chemical energy, electricity use can be better controlled.

Furthermore, an economic incentive rises from the price spreads of electricity prices on the various electricity markets in the Netherlands. An independent utility-scale battery energy storage facility could charge its assets during moments of high supply and low demand. These periods will result in a low electricity price. Discharging and selling electricity to the market can then happen when the electricity prices are high due to a higher load than the supply offers. Such periods of mismatch are likely to happen more often if the VRES keep on playing a more prominent role in the electricity system.

This research focused on finding optimized conditions and strategies to implement an independent large scale battery energy storage facility (BESF) for energy arbitrage purposes in the Netherlands. Based on optimization and simulation algorithms the maximum reachable profits and the economic viability are defined for various battery technologies and sizes.

A linear optimization function, bound by technical constraints that arise from operating a battery system and a certain set of assumptions, is used to identify the optimal battery technology and configuration to trade electricity on the Dutch power markets. Furthermore, an model predictive control (MPC) method is proposed to cope with the accuracy of electricity price forecasts.

As stated in the introduction in Chapter 1, this research aimed to answer the following research question:

'What are the technological and economic opportunities of energy arbitrage for large scale battery energy storage in the Netherlands?'

This question was divided into to the sub-questions mentioned below. Each item will be answered separately to be able to provide an answer to the main research question.

1. What are the most beneficial technological characteristics for a BESF?

   (a) What characteristics are most important?
   Round-trip efficiency, ramp rates, technical lifetime, CAPEX and OPEX all influence the operation and profitability of battery systems. From the research results it can be concluded that out of all technical characteristics, the high technical lifetimes play a very crucial role in the profitability of a BESF. The technical lifetime, both calendar and cycles based, determine how much capacity the battery loses per cycle. The revenues from energy arbitrage are generated with trading, and thus charging an discharging the system. Therefore, higher profits are achieved with a high number of cycles that can pass.

   Second, the C-rate of the system, which defines how much energy can flow in or out of the battery within one time step is an import measure to define the profitability of a BESF focusing on energy arbitrage. Each of the five technologies had their own ideal C-rate. Ranging from 0.8 per hour for Ni-Cd batteries to close to zero for high temperature and lead-acid batteries.

   Lastly, the costs of battery energy storage systems play a crucial role in determining profitability. The profitability is directly linked to operational and capital expenditures. Therefore, lowering the CAPEX and OPEX of the battery systems lead to a significant increase in economic viability.

   (b) What battery technology is the most beneficial?
   If technology and its configuration are optimal is determined by the profitability of the system. Four out of the five assessed battery technologies resulted to be not rewarding under the most ideal situation. Only the flow batteries result in positive numbers when looking at the energy arbitrage opportunities in combination with a perfect forecast. With an optimal C-rate of 0.55 and perfect foresight, the annual profit margin can reach 6% for a year with an 'average' price spread (2019). Despite its low efficiency, this battery technology clearly showed to be the most beneficial due to its high cycle life and relatively low costs.

   This leads to the conclusion that high technical lifetimes and low costs are the most influential and beneficial technological characteristics for utility-scale battery energy storage facilities for energy arbitrage purposes in the Netherlands. Efficiency does not show to have a significant effect on profitability. This lead to the results that flow batteries are the optimal available technology to operate the system with.

2. How could a BESF trade electricity on the different electricity markets in the Netherlands?
   First, in this research, it was defined that the DAM, FRR and FCR markets were the three most accessible market for a large-scale battery energy storage facility based on transparency, technical requirements and time scale.

   However, it has also been shown that in an optimized trading strategy the most significant opportunities to trade electricity in the Netherlands lay in the Frequency Restoration Reserve balancing market. This market has the biggest price spreads and allows the electricity price to become negative, which leads to revenues, even if the electricity is 'bought'. Nonetheless, the market size is limited and can quickly become saturated.

Furthermore, trading on the FCR market is shown to increase profitability. It can provide the battery facility with a base revenue which can reduce the investment risks of the facility. However, the maximum capacity that can be offered to this market is limited by the chosen system design and therefore can only offer a small contribution to the revenues if compared to participation in the FRR market. Furthermore, trading on the DAM does not result in high revenues. The prices spread on the market are very minimal compared to the imbalance market.

It has been shown that simulating one year of optimized operation of a battery facility can be done with a model predictive control method with a certain optimization horizon. It can be concluded that this method provides more thrust worthy insights into the economic viability of utility-scale battery energy storage for energy arbitrage purposes in the Netherlands compared to a perfect forecast optimization method. The proposed method can help to optimize charging patterns and bidding strategies for a fixed optimization over a certain forecast horizon. Further research can be done to bring the simulation closer to reality and minimize the number of uncertainties caused by certain assumptions.

3. What are the maximum profits reachable for an BESF with energy arbitrage?
   With an optimal trading strategy based on a real historical price data and a forecast horizon of a full year, the profits can be twice as high compared to operating the battery with a model predictive control strategy that has a limited forecast horizon. If errors in the forecast electricity prices are taken into account, the profits decreased even further. They would range from just 25% of the profits of the optimal strategy to negative results for a scenario with medium forecast errors.

   Based on the above-presented model predictive control model and its assumptions, the maximum reachable annual profit margin for a 200MWh/110Mw flow battery with a perfect forecast is -1% if costs of financing are taking into account. Therefore, it is not likely that a utility-scale flow battery in the Netherlands will be economically viable if used only for energy arbitrage.

   Nonetheless, the sketched scenario for 2030 shows more promising results. An annual profit margin of 10% is observed there, which would indicate that the investments are earned back after 10 years, which is half the calendar life of the flow battery. Furthermore, as discussed, future research could focus on assessing other use-cases next to energy arbitrage to seek opportunities for extra revenue streams.

In conclusion, it can be said that financial opportunities exist in the Netherlands regarding energy arbitrage. If not today, then in the future. It has been shown that towards 2030 the business case for battery energy storage will significantly increase due to decreasing capital costs of battery systems and forecast increasing price volatility due to the rise of the VRES and phase-out of fossil energy sources. The main challenge that can significantly increase the revenues is accurately forecasting electricity prices.

With this research, a contribution is delivered towards the realisation of commercially operating an independent utility-scale battery energy storage facility. Insights are provided on what battery technology is best suited for energy arbitrage purposes and the effectiveness of simulating the operation of a battery facility with a model predictive control method has been shown. This has lead to clearer insights into the profitability of operating a BESF in the Netherlands.

Bibliography

[1] S.R. Weart. *The Discovery of Global Warming.* Number 13 in New Histories of Science, Technology and Medicine. Harvard University Press, 2 edition, October 2008.

[2] The Guardian. Climate change. `https://www.theguardian.com/environment/climate-change`, 2019. [Online; accessed 21-Oct-2019].

[3] D. Carrington. The guardian: School climate strikes: 1.4 million people took part, say campaigners. `https://www.theguardian.com/environment/2019/mar/19/school-climate-strikes-more-than-1-million-took-part-say-campaigners-greta-thunberg`, May 2019. [Online; accessed 21-Oct-2019].

[4] Energy Transistions Commission. The challenge. `http://www.energy-transitions.org/the-challenge`. [Online; accessed 22-Oct-2019].

[5] Rijksoverheid. Klimaatakkoord, June 2019.

[6] Ministry of Economic Affairs. Energy report transition to sustainable energy. Technical report, Netherlands, Apr 2016.

[7] J.M. Eyer, J.J. Iannucci, and G.P. Gorey. Energy storage benefits and market analysis handbook - a study for the doe energy storage systems program. Technical report, Sandia National Laboratories, December 2004.

[8] IRENA. Utility-scale batteries - innovation landscape brief. Technical report, IRENA, September 2019.

[9] J.M. Eyer. Energy storage for the electricity grid: Benefits and market potential assessment guide. Technical report, Sandia National Laboratories, February 2010.

[10] IRENA. Electricity storage and renewables: Costs and markets to 2030. Technical report, IRENA, October 2017.

[11] S. Slingerland, N. Rothengatter, R. van der Veen, H. Bolscher, and K. Rademaekers. The balance of power – flexibility options for the dutch electricity market. Technical report, Triple E Consulting, Rotterdam, The Netherlands, April 2015.

[12] CBS. Aandeel hernieuwbare energie naar 7,4 procent. `https://www.cbs.nl/nl-nl/nieuws/2019/22/aandeel-hernieuwbare-energie-naar-7-4-procent`, May 2019. [Online; accessed 29-Oct-2019].

[13] Rijksoverheid. Hernieuwbare elektriciteit, 1990-2018. `https://www.clo.nl/indicatoren/nl0517-hernieuwbare-elektriciteit?ond=20881`, August 2019. [Online; accessed 29-Oct-2019].

[14] Rijksoverheid. Renewable energy use, 1990-2018. `https://www.clo.nl/en/indicators/en0385-renewable-energy-use`, September 2019. [Online; accessed 29-Oct-2019].

[15] CBS. Solar panel capacity up by more than half. `https://www.cbs.nl/en-gb/news/2019/17/solar-panel-capacity-up-by-more-than-half`, April 2019. [Online; accessed 29-Oct-2019].

[16] D. Metselaar. Vermogen zonnepanelen in nederland weer anderhalf keer hoger dan vorig jaar. `https://www.nrc.nl/nieuws/2020/01/29/vermogen-zonnepanelen-in-nederland-weer-anderhalf-keer-hoger-dan-vorig-jaar-a3988529`, Jan 2020. [Online; accessed 5 July 2020.

[17] B.N. Stram. Key challenges to expanding renewable energy. *Energy Policy*, 96:728–734, Sept 2016.

[18] Frontier Economics. Scenarios for the dutch electricity supply system. Technical report, Frontier Economics, London, September 2015.

[19] C. Kost, S. Shammugam, V. Jülch, H.-T. Nguyen, and T. Schlegl. Stromgestehungskosten erneuerbare energien. Technical report, Fraunhofer ISE, March 2018.

[20] TNO, Universiteit Utrecht Copernicus Instituut, and ECN. Naar een toekomstbestendig energiesysteem in nederland. Technical report, TNO, Delft, The Netherlands, March 2013.

[21] Rijksdienst voor Ondernemend Nederland. Sde+ najaar 2019. Technical report, RVO Nederland, Zwolle, The Netherlands, April 2019.

[22] F. Todd. Netherlands coal phase-out plans could lead to power deficit, warns expert. `https://www.nsenergybusiness.com/comment/netherlands-coal-phase-out-power-deficit/`, 2019. [Online; accessed 27-Jan-2020].

[23] Various authors on Flaticon.com. Free vector icons from flaticon. `https://www.flaticon.com/`, 2018. [Online; accessed 02-Dec-2019].

[24] TenneT. Annual market update 2018. Technical report, Tennet, March 2019.

[25] Imelda, M. Fripp, and M.J. Roberts. Variable pricing and the cost of renewable energy. Working Paper of The Economic Research Organisation at the University of Hawaii, May 2018.

[26] J. Cochran, M. Miller, O. Zinaman, M. Milligan, D. Arent, B. Palmintier, M. O'Malley, S. Mueller, E. Lannoye, A. Tuohy, B. Kujala, M. Sommer, H. Holttinen, J. Kiviluoma, and S.K. Soonee. Flexibility in 21st Century Power Systems. Technical report, National Renewable Energy Laboratory, May 2014.

[27] S.A.R. Mir Mohammadi Kooshkow and C.B. Davis. Business models design space for electricity storage systems: Case study of the netherlands. *Journal of Energy Storage*, 20:5950–604, Dec 2018.

[28] L. Sijtsma. The hybrid power plant. Masters thesis, TU Delft, March 2019.

[29] Next Kraftwerke. Balanshandhaving in het nederlandse elektriciteitsnet. `https://www.next-kraftwerke.nl/kennis/balanceringsenergie`, 2020. [Online; accessed 03-Apr-2020].

[30] TenneT. Fcr manual for bsps. Technical report, Tennet TSO B.V., November 2019.

[31] TenneT. Ancillary services. `https://www.tennet.eu/electricity-market/ancillary-services/`, 2020. [Online; accessed 24-Jun-2020].

[32] C. Yianni, G.E. Georghiou, and V. Efthymiou. Economic viability of battery energy storage for the provision of frequency regulation service. In *Economic Viability of Battery Energy Storage for the Provision of Frequency Regulation Service*. University of Cyprus, Aug 2018.

[33] ENTSO-E. Entso-e transparency platform. `https://transparency.entsoe.eu/`, 2020. [Online; accessed 12-Apr-2020].

[34] R.J.M. van Staveren. The role of electrical energy storage in a future sustainable electricity grid. Master thesis, TU Delft, Aug 2014.

[35] M. Mavrokapnidou. Modeling the interplay between storage and flexibility in power systems. Master thesis, TU Delft, Jul 2014.

[36] K. Sharma and D.V. Shah. Supercharged: Challenges and opportunities in global battery storage markets. Technical report, Deloitte, 2018.

[37] N.G. Paterakis, M. Gibescu, W. Kout, and Y.A. Hugo. Investigation of arbitrage between the dutch day-ahead and imbalance markets as a business case for the hydrogen bromine flow battery. *IEEE Manchester PowerTech*, pages 1–6, Jul 2017.

[38] L.J. de Vries and R.A. Verzijlbergh. How renewable energy is reshaping europe's electricity market design. *International Association for Energy Economics*, 7(2), 2018.

[39] B. Zakeri and S. Syri. Electrical energy storage systems: A comparative life cycle cost analysis. *Renewable and Sustainable Energy Reviews*, 42:569–596, Feb 2015.

[40] G.C. Gissey, P.E. Dodds, and J. Radcliffe. Market and regulatory barriers to electrical energy storage innovation. *Renewable and Sustainable Energy Reviews*, 82:781–790, Feb 2018.

[41] A.B. Gallo, J.R. Simoes-Moreira, H.K.M. Costa, M.M. Santos, and Em Moutinho dos Santos. Energy storage in the energy transition context: A technology review. *Renewable and Sustainable Energy Reviews*, 65:800–822, Nov 2016.

[42] B. Kibrit. Pumped hydropower storage in the netherlands. master's thesis, Delft University of Technology, 2013.

[43] X. Luo, J. Wang, M. Dooner, and J. Clarke. Overview of current development in electrical energy storage technologies and the application potential in power system operation. *Applied Energy*, 137:511–536, Jan 2015.

[44] F. Teng and G. Strbac. Business cases for energy storage with multiple service provision. *Journal of Modern Power Systems and Clean Energy*, 4:615–625, Oct 2016.

[45] A. Stephan, B. Battke, M.D. Beuse, J.H. Clausdeinken, and T.S. Schmidt. Limiting the public cost of stationary battery deployment by combining applications. *Nature Energy*, 1, May 2016.

[46] O. Schmidt, S. Melchior, A. Hawkes, and I. Staffell. Projecting the future levelized cost of electricity storage technologies. *Joule*, 3:81–100, Jan 2019.

[47] P. Nikolaidis and A. Poullikkas. Cost metrics of electrical energy storage technologies in potential power system operations. *Sustainable Energy Technologies and Assessments*, 25:43–58, Feb 2018.

[48] C. Brivio, S. Mandelli, and M. Merlo. Battery energy storage system for primary control reserve and energy arbitrage. *Sustainable Energy, Grids and Networks*, 6:152–165, Jun 2016.

[49] H. Wang and B. Zhang. Energy storage arbitrage in real-time markets via reinforcement learning. *2018 IEEE PES General Meeting Cornell University*, Nov 2017.

[50] Hortileads. Grote batterijen nieuwe spelers op de onbalans- en fcr-markt. `https://www.onderglas.nl/grote-batterijen-nieuwe-spelers-op-de-onbalans-en-fcr-markt/`, 2018. [Online; accessed 04-Nov-2019].

[51] J. Wang, T. Xu, H. Li, and T. Ma. Recent progress of silicon composites as anode materials for secondary batteries. *RSC Advances*, 6:87778–87790, Aug 2016.

[52] MIT Electric Vehicle Team. A guide to understanding battery specifications. Technical report, MIT, Dec 2008.

[53] H. Beltran, I.T. Garcia, J.C. ALfonso-Gil, and E. Perez. Levelized cost of storage for li-ion batteries used in pv power plants for ramp-rate control. *IEEE*, 34:554–561, Mar 2019.

[54] Hornsdale Power Reserve. Hornsdale power reserve australia. `https://hornsdalepowerreserve.com.au/`, 2020. [Online; accessed 10 July 2020.

[55] Wikipedia. Flow battery. `https://en.wikipedia.org/wiki/Flow_battery`, 2020. [Online; accessed 24-Jun-2020].

[56] TenneT. Electricity storage tool. `https://www.tennet.eu/electricity-market/dutch-market/electricity-storage-tool/`, 2018. [Online; accessed 14-Apr-2020].

[57] Gorinevsk. Lecture 14 - model predictive control - part 1: The concept. `https://web.stanford.edu/class/archive/ee/ee392m/ee392m.1056/Lecture14_MPC.pdf`, June 2005. [Online; accessed 2 July 2020.

[58] M. Khalid and A.V. Savkin. An optimal operation of wind energy storage system for frequency control based on model predictive control. *Renewable Energy*, 48:127–132, Dec 2012.

[59] C.V. Rao and J.B. Rawlings. Linear programming and model predictive control. *Journal of Process Control*, 10:283–289, Apr 2000.

[60] Mahraz Amini and Mads Almassalkhi. Optimal corrective dispatch of uncertain virtual energy storage systems. *IEEE Transactions on Smart Grids*, pages 1–1, Mar 2020.

[61] D. Rosewater, R. Baldick, and S. Santoso. Risk-averse model predictive control design for battery energy storage systems. *IEEE Transactions on Smart Grids*, pages 1–1, Oct 2019.

[62] L. McCurlie, M. Preindl, and A. Emadi. Fast model predictive control for redistributive lithium ion battery balancing. *IEEE Transactions on Industrial Electronics*, 64:1350–1357, Feb 2017.

[63] R. Suresh and R. Rengaswamy. Modeling and control of battery systems. part ii: A model predictive controller for optimal charging. *Computers & Chemical Engineering*, 119:326–335, Nov 2018.

[64] C. Zou, C. Manzie, and D. Nesic. Model predictive control for lithium-ion battery optimal charging. *IEEE*, 23:947–957, Apr 2018.

[65] D. Kiedanski, M.U. Hashmi, A. Busic, and D. Kofman. Sensitivity to forecast errors in energy storage arbitrage for residential consumers. pages 1–7. IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids, Oct 2019.

[66] J. Hu, Y. Xu, K.W. Cheng, and J.M. Guerrero. A model predictive control strategy of pv-battery microgrid under variable power generations and load conditions. *Applied Energy*, 221:195–203, Jul 2018.

[67] G. Kujundzic, S. Iles, J. Matusko, and M. Vasak. Optimal charging of valve-regulated lead-acid batteries based on model predictive control. *Applied Energy*, 187:189–202, Feb 2017.

[68] T. Morstyn, B. Hredzak, R.P. Aguilera, and V.G. Agelidis. Model predictive control for distributed microgrid battery energy storage systems. *IEEE*, 26:1107–1114, May 2018.

[69] J. Sachs and O. Sawodny. A two-stage model predictive control strategy for economic diesel-pv-battery island microgrid operation in rural areas. *IEEE*, 7:903–913, Jul 2016.

[70] X. Zhang, J. Bao, R. Wang, C. Zheng, and M. Skyllas-Kazacos. Dissipativity based distributed economic model predictive control for residential microgrids with renewable energy generation and battery energy storage. *Renewable Energy*, 100:18–34, Jan 2017.

[71] B. Zhu, H. Tazvinga, and X. Xia. Switched model predictive control for energy dispatching of a photovoltaic-diesel-battery hybrid power system. *IEEE*, 23:1229–1236, May 2015.

[72] N. Tian, H. Fang, and Y. Wang. Real-time optimal charging for lithium-ion batteries via explicit model predictive control. pages 2001–2006. 2019 IEEE 28th International Symposium on Industrial Electronics, Aug 2019.

[73] M. Torchio, N.A. Wolff, D.M. Raimondo, L. Magni, and U. Krewer. Real-time model predictive control for the optimal charging of a lithium-ion battery. pages 4536–4541. 2015 American Control Conference (ACC), Jul 2015.

[74] M. Arnold and G. Andersson. Model predictive control of energy storage including uncertain forecasts. Technical report, ETH Zurich, 2011.

[75] R. Halvgaard. Model predictive control for smart energy systems. Masters thesis, Technical University of Denmark, Feb 2014.

[76] M.U. Hashmi, A. Mukhopadhyay, A. Busic, and J. Elias. Optimal storage arbitrage under net metering using linear programming. pages 1–7. 2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids, Oct 2019.

[77] M. Khalid and A.V. Savkin. A model predictive control approach to the problem of wind power smoothing with controlled battery storage. *Renewable Energy*, 35:1520–1526, Jul 2010.

[78] A. Khatamianfar, M. Khalid, A.V. Savkin, and V.G. Agelidis. Improving wind farm dispatch in the australian electricity market with battery energy storage using model predictive control. *IEEE*, 4:745–755, Jul 2013.

[79] K. Bradbury, L. Pratson, and D. Patino-Echeverri. Economic viability of energy storage systems based on price arbitrage potential in real-time u.s. electricity markets. *Applied Energy*, pages 512–519, Feb 2014.

[80] Wikipedia. Monte carlo method. `https://en.wikipedia.org/wiki/Monte_Carlo_method`, 2020. [Online; accessed 6 July 2020.

[81] V. Jülch. Comparison of electricity storage options using levelized cost of storage (lcos) method. *Applied Energy*, 183:1594–1606, Dec 2016.

[82] H.J. Bijl. Techno-economic analysis of energy storage systems for offshore wind farms. Bachelor thesis, RU Groningen, April 2019.

[83] Q. Yu, R. Xiong, R. Wang, and C. Lin. A comparative study on open circuit voltage models for lithium-ion batteries. *Chinese Journal of Mechanical Engineering*, 31, Nov 2018.

[84] F. Wankmuller, P.R. Thimmapuram, K.G. Gallagher, and A. Botterud. Impact of battery degradation on energy arbitrage revenue of grid-level energy storage. *Journal of Energy Storage*, 10:55–66, Apr 2017.

[85] J. Engels, B. Claessens, and G. Deconinck. Techno-economic analysis and optimal control of battery storage for frequency control services, applied to the german market. *Preprint for Applied Energy*, Mar 2019.

[86] D. Connolly, H. Lund, P. Finn, B.V. Mathiesen, and M. Leahy. Practical operation strategies for pumped hydroelectric energy storage (phes) utilising electricity price arbitrage. *Energy Policy*, 39:4189–4196, Jul 2011.

[87] S.K. Aggarwal, L.M. Saini, and A. Kumar. Electricity price forecasting in deregulated markets: A review and evaluation. *International Journal of Electrical Power & Energy Systems*, 31:13–22, Jan 2009.

[88] M. Afman, S. Hers, and T. Scholten. Energy and electricity price scenarios 2020-2023-2030. Technical report, CE Delft, January 2017.

[89] R. Sioshansi, P. Denholm, and T. Jenkin. A comparative analysis of the value of pure and hybrid electricity storage. *Energy Economics*, 33:56–66, Jan 2011.

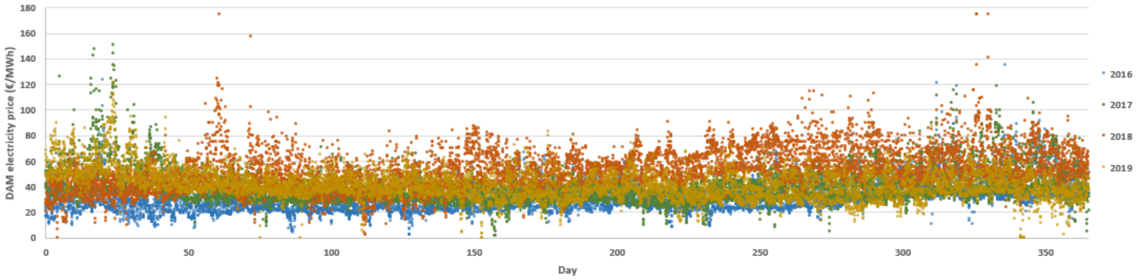
A | List of symbols

Symbol	**Unit**	**Description**
$Profit$	€	Amount of profit generated over $\mathrm{t_{tot}}$
t	-	Present time step ($t \in 1, 2, \ldots t_{tot}$)
t_{tot}	-	Total simulated time steps (if 15-min time steps $t_{tot} = 35040$ for a year)
$V_{DAM,sell,t}$	MWh	Amount of electricity sold at the DAM at time step t
$P_{DAM,t}$	$€/MWh$	Electricity price at the DAM at time step t
$V_{aFRR,sell,t}$	MWh	Amount of electricity sold at the aFRR market at time step t
$P_{aFRR,up,t}$	$€/MWh$	Electricity price at the aFRR-up market at time step t
$V_{DAM,buy,t}$	MWh	Amount of electricity bought at the DAM at time step t
$V_{aFRR,buy,t}$	MWh	Amount of electricity bought at the aFRR market at time step t
$P_{aFRR,down,t}$	$€/MWh$	Electricity price at the aFRR-down market at time step t
$CAPEX_{MWh}$	$€/MWh$	Installation costs of the facility per MWh installed
$CAPEX_{MW}$	$€/MW$	Installation costs of the facility per MW installed
V_{max}	MWh	Total installed energy volume
$Power\ Cap$	MW	Total installed power capacity
LT	-	Technical lifetime in number of time steps
$OPEX$	$€/(MWh * y)$	Operational expenditures including grid costs
$V_{in,t}$	MWh	Amount of electricity fed in (charged) to the BESF at step t
$V_{out,t}$	MWh	Amount of electricity fed out (discharged) of the BESF at step t
η	%	Efficiency
η_{disch}	%	Discharge efficiency
η_{ch}	%	Charge efficiency
$CBCP$	MWh	Maximum cable capacity of the cable between the grid and the BESF
$\%_R$	%	Maximum ramp per time step
$C - rate$	1/h	Ratio of power capacity to energy capacity
V_t	MWh	State of charge at time step t
SOC_{min}	%	Minimal state of charge
SOC_{max}	%	Maximum state of charge
$Cap.fade_t$	MWh	Faded capacity due to cycling at time step t
$\%_{Cap.fade}$	%	Maximum capacity loss at end of life
CL	MWh	Technical lifetime in number of charge cycles
$\%_{V_0}$	%	Initial SOC
$Revenue$	€	Amount of net revenue generated
$Forecast\ P_{DAM}$	$€/MWh$	Electricity price forecast at the DAM
$Forecast\ P_{aFRR,up}$	$€/MWh$	Electricity price forecast at the aFRR-up market
$Forecast\ P_{aFRR,down}$	$€/MWh$	Electricity price forecast at the aFRR-down market
$\%_{FCR}$	%	Share of reserved energy capacity for the FCR market
$FCR_{capacity}$	MWh	Reserved amount of energy capacity for the FCR market
n	-	Present time step ($n \in 1, 2, \ldots n_{tot}$)
n_{tot}	-	Total simulated time steps (if 15-min time steps $n_{tot} = 35040$ for one year)
z	-	Time step indicator for the FCR market ($z \in 1, 2, \ldots n_{tot}$)
$FCR\,CAP$	MW	Reserved amount of power capacity for the FCR market
P_{FCR}	$€/MW$	Electricity price at the FCR market
r	%	Interest rate
i	%	Discount rate
$LCOS$	$€/MWh$	Levelised cost of storage
$WACC$	%	Weighted average cost of capital
E	€	Value of equity
D	€	Value of debts
R_e	€	Costs of equity
R_d	€	Costs of debts
T	%	Corporate tax rate

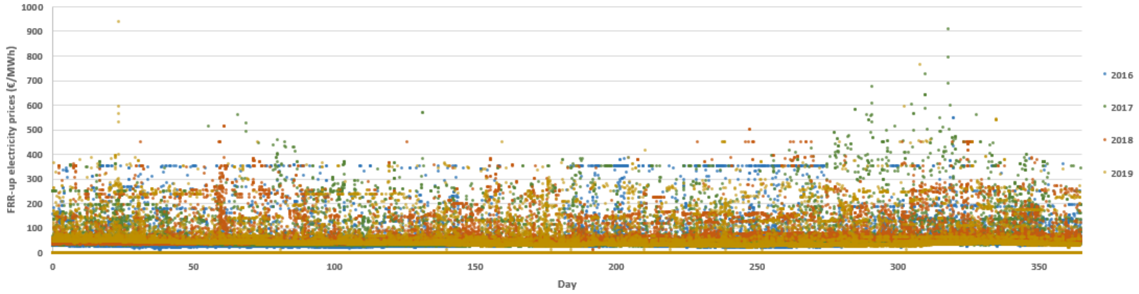
B | Price data comparison

In the optimization part of this research, comparisons are made between the results based on price data for different years. The years included are 2016 to 2019. This appendix gives an overview of the key indicators of the price data characteristics and compares them.

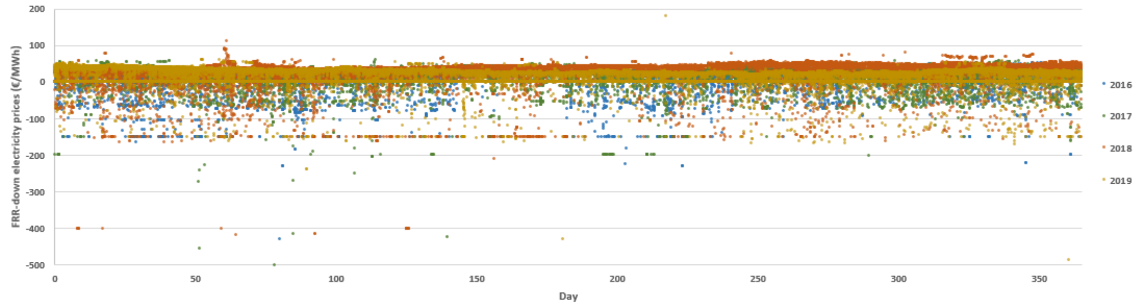
The complete data sets of the DAM, FRR-up and FRR-down prices are shown in Figure B.1. It give a grasp overview of the price spreads of the markets for the different markets.



(a) Price data of DAM.



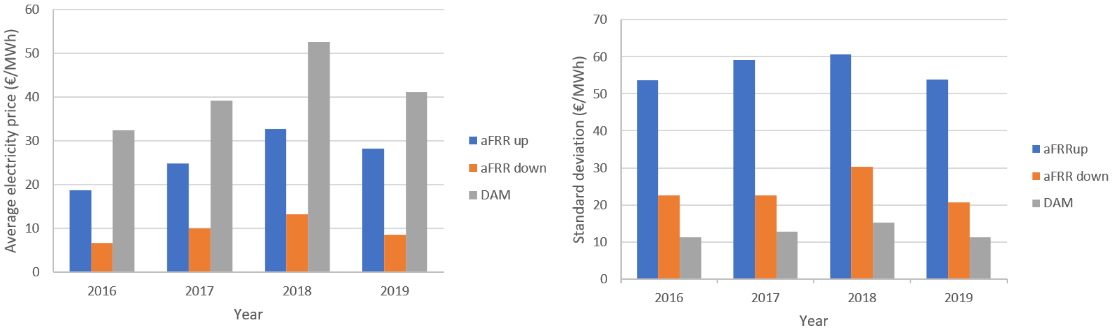
(b) Price data of FRR-up market.



(c) Price data of of FRR-down market.

Figure B.1: Price data of DAM, FRR-up and FRR-down markets for 2016 to 2019.

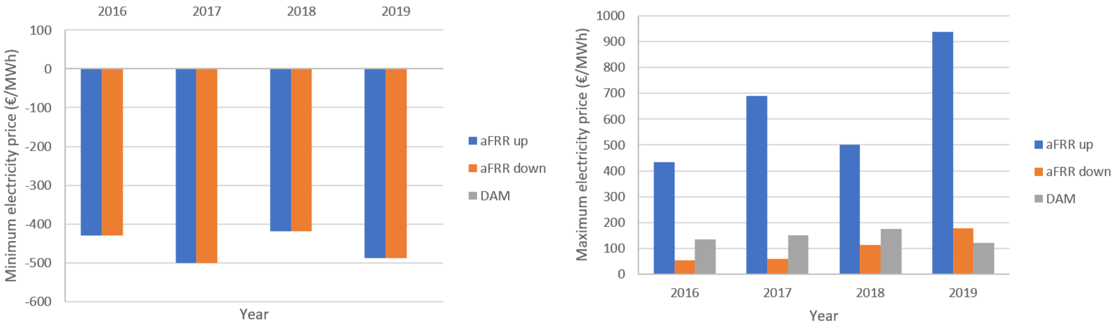
The standard deviation and average prices over the years are shown in Figure B.2. As can be seen the standard deviations on the aFRR markets are significantly higher then for the DAM. This is especially the case for the 'up' market, which is aimed to supply electricity to the grid and hence selling electricity of the BESF. Looking at the average electricity prices, the 'aFRR down' price is the lowest for all years and the DAM prices are highest.



(a) Yearly average. **(b) Yearly standard deviation.**

Figure B.2: Yearly average electricity price and the standard deviations of the price data.

The minimum and maximum prices are shown in Figure B.3. While minimum prices are fairly constant over the year for all three assessed electricity markets, the maximum price of the aFRR down market seems to be increasing over the years. Furthermore, the maximum aFRR down price exceeds the maximum DAM price in 2019.



(a) Minimum electricity price. **(b) Maximum electricity price.**

Figure B.3: Minimum and maximum electricity prices. Note: the minimum electricity price on the DAM is around zero €/MWh every year.

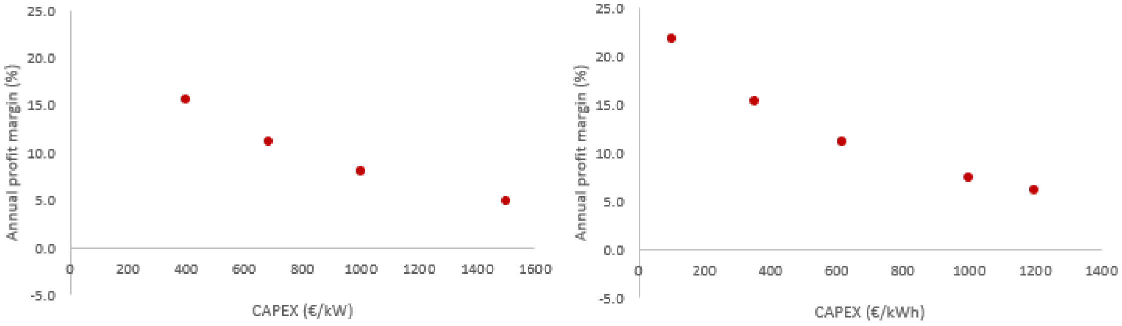
Moreover, the minimum electricity price of the aFRR up and down markets are almost equal. On the contrary, the maximum prices show very significant differences between the markets.

All together, it can be said that the major characteristics of the electricity prices of the markets are relatively constant throughout the four years. Based on the above presented data it could be concluded that trading electricity for the BESF on the aFRR market is more beneficial than on the DAM due to the significant price deviations. Price differences are beneficial for the business case of the BESF since those create the revenues. Furthermore, buying electricity would be most viable on the aFRR markets because of the low average prices and the prices regularly drop below zero. Selling electricity would be beneficial on both the DAM and aFRR up markets. Since the DAM has a high average electricity price and the aFRR shows very high price spikes.

C | Sensitivity analysis

This appendix holds the result of the sensitivity analysis for the linear optimization model and the model predictive control method. The annual profit margin is set out against the various technological characteristics.

In Figure C.1, the effects of an increasing CAPEX on the profitability of the storage facility. As expected, increasing the capacity based CAPEX reduces the annual profit margin. This is conform the design of the objective function of the model and shows the direct result of the fact that a higher installed power capacity, does not result in a higher revenue in the optimization model. Furthermore, the increasing the volume based CAPEX also reduces the profitability. Both curves flatten out when reaching significant large values, which would indicate that the higher the CAPEX get, the less impact it has on the profit margin. However, at the same time the annual profit margins are approaching zero when significantly increasing the CAPEX. It is important to note that based on the presented model, the amount of traded electricity does not change with increasing costs. The model optimizes to the trading strategy with the objective to maximize the revenues from trading electricity. Therefore, the revenue from trading electricity remains constant when changing the CAPEX and OPEX of the system. However, increasing the systems costs do decrease the profit margins.



(a) Effect of varying capacity based CAPEX on the annual profit margin.

(b) Effect of varying volume based CAPEX on the annual profit margin.

Figure C.1: Effect of varying CAPEX on the annual profit margin.

The graph on the OPEX of the system in C.2, shows a linear decay. A linear decrease in profit margin is observed with increasing OPEX. This can be explained by the fact that the annual costs are a separate factor in the linear objective function. A 50% decrease in OPEX leads to a 38% increase in annual profit margin.

In Figure C.3 the technical lifetime effects on the profitability of the BESF are shown. Regarding the cycling life, it can be said that a higher cycling life results in a higher profit. As for the calendar lifetime in years, a clear maximum can be seen. The ideal calendar life would be around 20 years, if the cycle life is kept constant at 50,000 cycles. It can be seen that up to 20 years, the calendar life is the limiting factor. If the calendar life becomes longer then 20 year, the cycling life becomes limiting and hence a bigger technical life time does not increase the profit margin anymore. In Section 4.1.5, a Monte Carlo analysis is done to give more in-depth knowledge of the sensitivity of the model to the cycling and calendar life of the battery system.

In Figure C.4a (next page) the effects of increasing the efficiency are presented. As expected higher efficiencies result in higher profits. Higher efficiencies reduce the losses between a traded

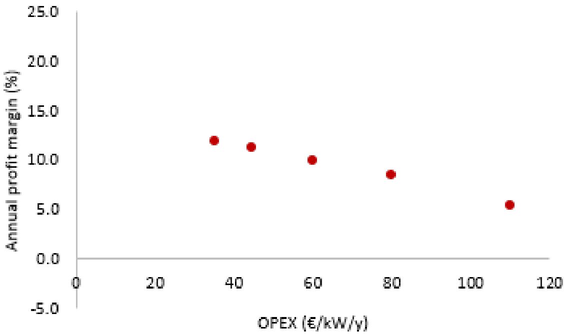
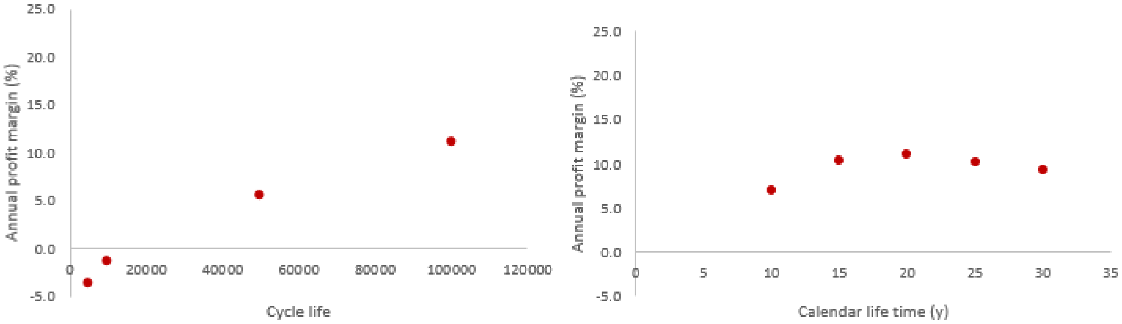


Figure C.2: Effect of varying OPEX on the annual profit margin.



(a) Effect of varying cycling life time on the annual profit margin.

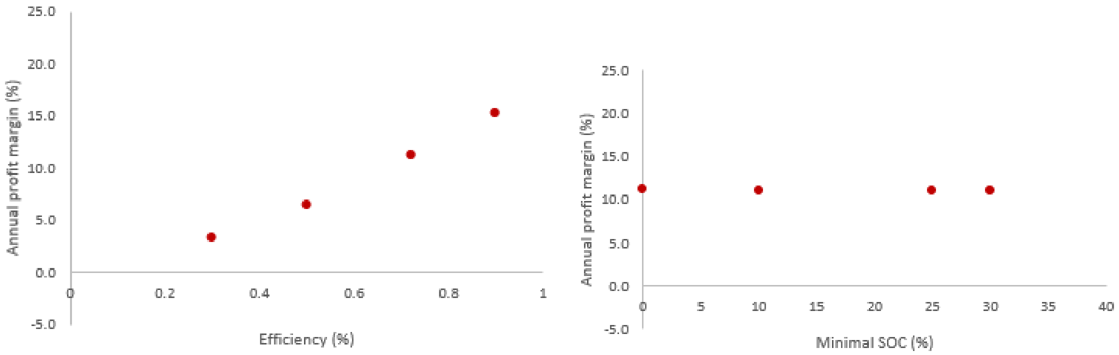
(b) Effect of varying technical life time on the annual profit margin.

Figure C.3: Effect of varying technical and cycling life time on the annual profit margin.

energy flows and an energy flow to or from the battery system. Due to the extensive research into batteries, it is expected that efficiencies will keep on increasing in the coming year. That would be a beneficial feature for the economic viability of energy arbitrage with a battery system. However, overall efficiencies of the various battery technology are all already above 70%. The Li-ion battery for example already has an efficiency of 95%. Therefore, not too much margin for improvement is possible there.

Lastly, Figure C.4b (next page) shows the very limited impact of the minimal SOC of the battery on the profit margin. Almost no, effect can be observed. This can be explained by the fact that the maximum ramp rate is much smaller than the total battery volume. Therefore, in one time step only a small part of the energy volume can be charged or discharged. If the battery could fully discharge in one time step, the limit of traded energy in one step, would be determined by the SOC limits. However, now this is limited by the ramping capacities of the BESF.

From the presented data, it can be concluded that efficiency, cycle and calendar life and energy based CAPEX have the most significant impact on the annual profit margin. Improvements in



(a) Effect of varying efficiency on the annual profit margin.

(b) Effect of varying minimal SOC on the annual profit margin.

Figure C.4: Effect of varying efficiency and minimal SOC on the annual profit margin.

these technical parameters are highly beneficial for the profitability of a utility scale battery energy storage facility. On the other hand, OPEX and minimal SOC are shown to have a less significant impact on the economic viability when optimized with the presented linear optimization model of this research.