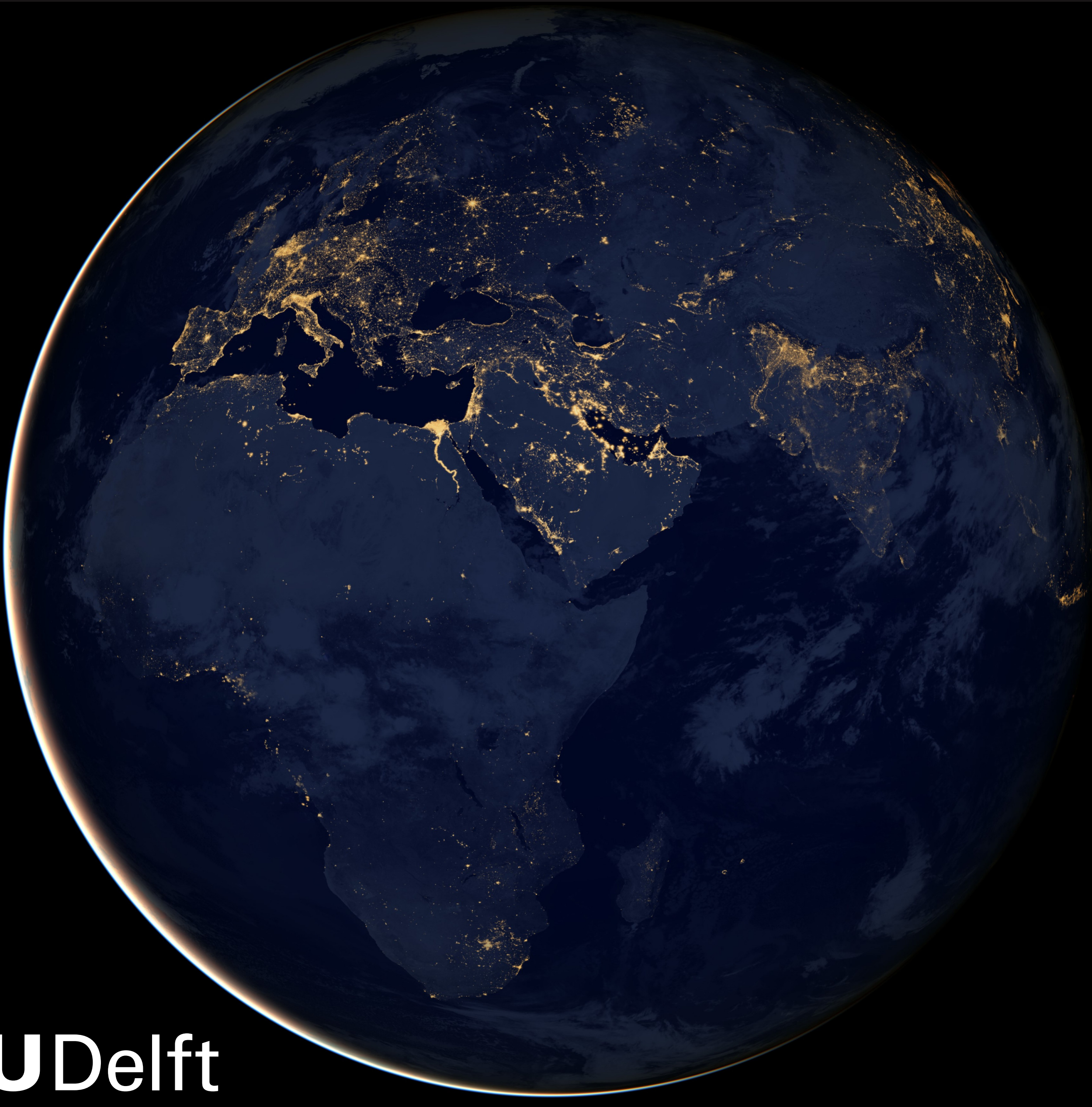
Energy Storage System Modelling

Modelling the influence of large-scale profit optimising energy storage systems participating in both energy and balancing markets

Ruben Siemensma



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by

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Preface

This thesis, ”Energy Storage System Modelling”, is a branch of the more extensive assignment ”modelling a 100 % renewable grid”. This assignment was done under the research group intelligent electrical power grids within the TU Delft. The thesis was written to graduate from my electrical power engineering studies.

Modelling a 100% renewable grid was a subject that immediately resonated with me. After discussing the topic with my thesis advisor Dr M. Cvetkovic, we converged the topic into the role and modelling of energy storage systems within energy systems. Defining the exact details and goals of the thesis came later in time, as at the start of the project, much freedom was given to investigate energy storage systems from multiple angles. In the end, converging this broad subject into a proper thesis with clear, achievable goals and outcomes was possible.

Firstly I would like to thank Dr M. Cvetkovic for the fantastic project, advice, feedback and freedom given to me, for helping me keep my head cool and for giving me confidence in successfully completing the thesis. Secondly, I would like to thank both Dr M. Cvetkovic and Prof. dr. P. Palensky for showing great enthusiasm towards this project and thereby giving me lots of energy and more confidence in a successful end result. Lastly, I thank my friends and family, who helped me with valuable advice and concrete suggestions for improving my thesis.

Ruben Siemensma
Pingjum, August 2022

Abstract

As the share of renewable energy generation increases, the need for energy storage also increases. Therefore, there is a need for better storage representation in the current energy modelling tools. In the present day, the longer-term energy storage systems are not fully represented since, for existing storage systems, the self-serving nature of these leads to participation in multiple energy markets. This is because participating in other markets, like the balancing markets, can lead to higher overall profits than a storage system only participating in the wholesale market. This thesis investigates different energy storage technologies and multiple prominent storage applications for grids. Furthermore, an overview of the European energy markets will be examined, and different design options will be discussed. These markets include frequency containment reserve (FCR), frequency regulation reserves (aFRR/mFRR) and the wholesale markets. The review of storage technologies, applications, and available markets has led to the development and simulation of single-purpose energy storage models fulfilling grid applications. By combining the specific purpose models, a complete energy market and energy storage model representation could be created. The model created is unique since the complete energy system model allows energy storage systems to optimally dispatch over multiple markets while at the same time also influencing these markets. Multiple cases were investigated using this model, such as the influence of increasing storage capacity on the wholesale and balancing market and the influence of storage systems just performing one service, so only regulation, arbitrage or peak-shaving. Based on the model results, recommendations are made on improving the current energy market designs and how to better represent storage systems in existing energy system models.

Keywords: DAM, aFRR, mFRR, FCR, peak-shaving, MPC, ESOM, storage applications, storage modelling, storage technologies, ESOM, wholesale market, balancing market.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
MPC	Model Predictive Control
ESOM	Energy System Optimization Model
BESS	Battery Energy Storage Systems
ESS	Energy Storage Systems
VR	Vanadium Redox Flow Battery
MILP	Mixed Integer Linear Programming
SOC	State of Charge
CEAS	Compressed Air Energy Storage
BSP	Balance Service Provider
BRP	Balance Responsible Party
RQ	Research Question

Symbols

Symbol	Definition	Unit
SOC	State of charge	[N/A]
η	Efficiency	[%]
MC	Marginal cost	[Euro/MWh]
C	Cost	[Euro/MW]
λ	Price	[Euro/MWh]/[Euro/MW]
P	Power output	[MW]

Superscripts

Symbol	Definition
dam	Day-ahead market
E	Energy clearing
C	Capacity clearing
up $\uparrow$	Upwards
$down$ $\downarrow$	Downwards
gen	Thermal generator
st	Storage system
dch	Discharging
ch	Charging
rte	Round trip efficiency
$SDrate$	Self-discharge rate

Subscripts

Symbol	Definition
t, k	Time steps
i, j	Unit entries

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1 Introduction

Past trends show an ever-increasing penetration of renewable sources [1]. Moreover, in the IPCC climate report, the need for rapid CO_2 reduction is urgent to prevent unchangeable ecological damage [2]. Therefore the need for more renewable generation in the future is imperative. This need eventually leads to the question: How to model a 100% renewable grid. An essential need in such a renewable electricity grid is large amounts of electric energy storage. This thesis will look at the modelling principles of large energy storage systems, the impact on the electricity grid, and the influence on multiple energy markets.

Energy storage systems can play an essential role in future energy systems. Therefore, there is a need for long-term storage models which enables long-term storage investment decisions. To partly provide a solution to this need, the scope of this thesis will mainly focus on the long-term representation of storage systems, therefore representing energy systems which include large quantities of energy storage capacity.

A review from 2012 [3] looked at the representation of flexibility options in energy modelling tools. One of these options is energy storage. The best energy storage representation among energy modelling tools considered in the review is provided by Transient and PyPsa. From these two, transiEnt is a modelling tool based on differential and algebraic equations using Modelica programming language. Further is stated that the scope of TransiEnt is in the seconds [4]. These reasons show that TransiEnt is too detailed and therefore falls outside this thesis's time window since the goal is to better enable longer-term energy storage decisions. PyPsa is quite fit to perform long-term investment decision modelling and optimisation-based modelling. Also, according to the source, the representation of the energy storage systems in PyPsa is good. However, upon further investigation, it appears that also PyPsa has its limitations, as physical phenomena like cycle ageing and calendrical ageing are not included by default in these models. Furthermore, PyPsa does not represent the opportunity costs of energy storage systems since storage systems are capable of obtaining revenue from multiple sources. These revenue sources can be from multiple ancillary services, which are essential services required to ensure that generated electric energy can be correctly distributed to consumers. Currently, in PyPsa, the energy storage system's goal is to minimise overall system costs, therefore only participating in the wholesale market. The wholesale market is where most of the energy is being traded. In practice, these storage systems will operate selfishly and provide multiple services to maximise profits.

A part of the gap that this thesis tries to overcome is the underrepresentation of some of these opportunity costs in long-term energy system models. This gap mainly concerns the opportunity costs from the balancing market but also represents the self-serving nature of storage systems, both of which are not yet well represented in the long-term energy system models.

The structure of this thesis is as follows. The thesis starts with a problem statement and research questions, followed by the chapter "storage technologies and applications" (chapter 3). This chapter

will cover the functioning of energy storage systems in two ways: first, by going into the technical functioning of different storage technologies and laying out the different parameters, and second, by investigating many different services storage systems can provide to the energy grid.
In chapter 4, the European energy markets are discussed, such as the wholesale markets consisting of the day-ahead and intraday market but also the balancing markets comprising of the frequency containment reserve market (FCR) and the frequency regulation reserve markets (aFRR/mFRR). The balancing markets are responsible for keeping the demand and generation equal closer to real-time operation. This chapter will further examine how these markets are defined.
Chapter 5 discusses different types of single-purpose energy storage models. Single-purpose energy storage models mean that these models only model one or at most two ancillary service(s). These models are first introduced conceptually and are then implemented in simulation, tested and compared to other models, including comparisons with other energy system optimisation models such as PyPsa. The modelling of these storage applications has been done using different approaches, such as system level or unit level approaches, which in this thesis are commonly referred to as the lower-level problem (LLP) and the upper-level problem (ULP), respectively.
By combining some of the smaller single-purpose models, a more comprehensive complete energy system model has been made, covered in chapter 6. In chapter 6, the implemented design of the energy markets is given, followed by the bidding strategies of both the thermal generators and energy storage systems. The complete energy system model is simulated using different scenarios. These scenarios are differentiated based on storage size, storage technology and applications. Based on these results, recommendations are made to improve storage representation in existing energy system optimisation modelling tools. Finally, the thesis concludes by summarizing the findings, reflecting on the thesis process and introducing future work.

2 Problem Statement

The problem statement is given as:

How to better represent the influence of large-scale self-serving energy storage systems in existing models and to enable making better informed long-term investment decisions.

To further elaborate on this statement, currently, in most energy storage models, storage systems are used to minimise total system costs. However, these models do not consider the storage system's desire to maximise income, which can come from multiple sources, including the balancing market. Here, the goal is to better represent these other income sources in the existing models, making it easier to make long-term predictions and thus investment decisions.

2.1. Research questions

The problem statement is subdivided into multiple research questions (annotated by [RQ-X]) given below:

RQ-1 How will profit maximising energy storage systems participate and influence the wholesale and balancing market?

RQ-2 How will energy storage systems performing ancillary services, like regulation, influence demand and energy markets, and how can influence be represented?

RQ-3 How will energy systems be influenced by storage systems prioritising profit maximisation over total system cost minimisation?

RQ-4 Which different energy storage modelling methods can be used to model energy storage applications such as ancillary services, arbitrage and peak-shaving?

RQ-5 How to introduce and simulate the influence of storage systems participating in other markets into existing models such as PyPsa?

RQ-6 What is the impact on the wholesale market and demand if storage systems can only perform one application and, for example, only perform arbitrage, (frequency) regulation or peak-shaving?

[RQ-1] covers the impact of storage systems on the different markets, so here it is being looked at when markets start to saturate and how the storage systems influence energy prices.
The objective of [RQ-2] is to create a clearer picture of the influence of the different ancillary services on the total system. So the influence of charging and discharging the storage system in order to keep providing said service.
The objective of [RQ-3] is to investigate if there are differences in behaviour and influence on the energy systems. This can be achieved by looking at energy systems models driven by minimizing the total system costs versus energy systems models driven by prioritizing maximizing the profit of storage systems.
[RQ-4] looks at the different ways many applications of storage systems can be modelled since there are multiple methodologies to model and represent these services.

The goal of [RQ-5] is to find a more straightforward way to represent the influence of large-scale storage systems being applied for multiple services. Moreover, provide an easy solution to include this influence in other energy system optimization tools.
Finally, the objective of [RQ-6] is to investigate the differences between equal energy systems if the installed storage systems only perform one specific application.

2.2. Objectives

The objectives of this thesis are listed below:

1. To create simplified models that can describe specific storage grid services.
2. To create an energy system representation with generators and multiple markets.
3. To create an energy storage model which optimally participates in the available energy system markets.

3

Storage Technologies and Applications

This chapter is subdivided into two sections. The first section will discuss energy storage applications, which answers the question: what services can a storage system provide to the energy system? The second section, ”energy storage technologies”, investigates different storage technologies.

3.1. Energy storage applications

Storage systems can provide a large number of different grid services. Many models that include energy storage systems tend to only look at energy storage systems as a means to store excess electricity from renewable generation or perform arbitrage. However, the most significant part of the income from an energy storage system will come from ancillary services, like regulation. This section summarises and briefly explains all the different services a storage system can provide. In a study from 2013 [5], a comprehensive overview is given of most of the different services a storage system can provide. These different services are visualised and summarised in Figure 3.1. As can be seen in the figure, the different services are sorted based on relative storage system size and physical location in the energy network. The upstream services which require larger-scale storage systems are more to the left in the figure, and the generally smaller downstream storage systems are more to the right. Since this study covers these services in great detail, this thesis will only briefly conceptually describe these grid services.

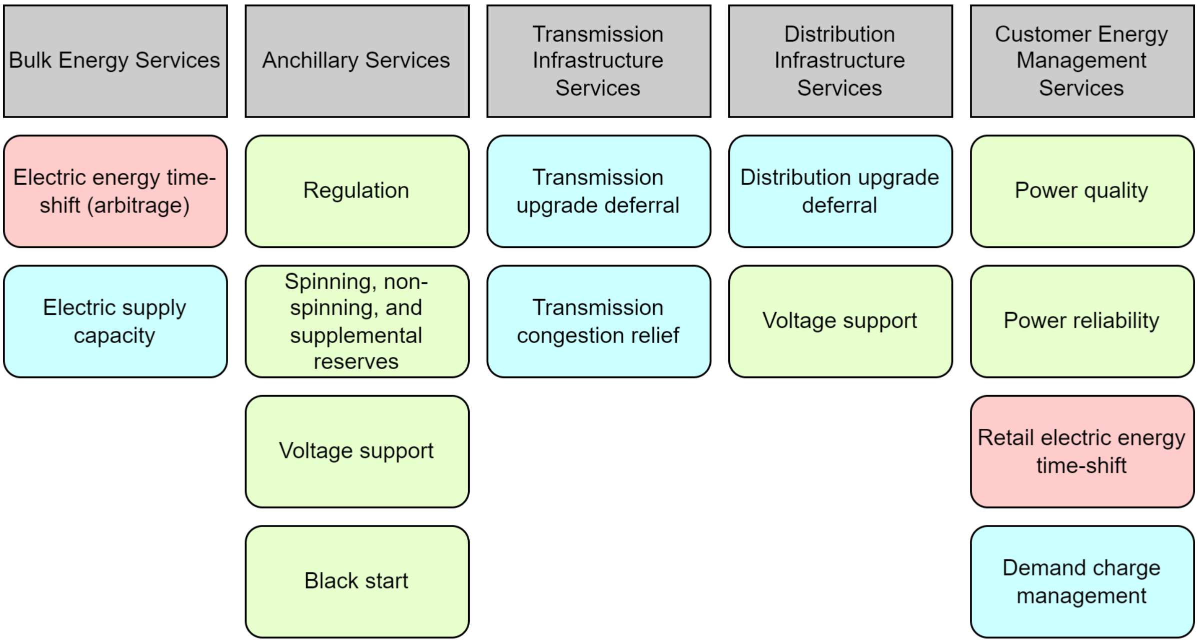

Figure 3.1: An overview of services energy storage systems can provide (Adapted from:[6]), with in red the arbitrage type services, in green the power quality type services, and in blue the peak-shaving type services.

3.1.1. Bulk energy services

The largest energy storage systems generally provide bulk energy services, for instance, pumped hydro and Compressed Air Energy Storage (CAES). Currently, pumped hydro storage has the largest share in energy storage systems, with its primary use being energy time-shifting and, to a lesser extent, electric supply capacity services [7]. In the following sub-sections, these bulk energy services will be further discussed.

Electric energy time shift (arbitrage)

Electric energy time-shift (arbitrage) is a service that entails both energy trading and excess renewable energy storage. To further explicate: the central concept of this service is purchasing electric energy when electricity prices are low, thus storing it in the energy storage system (ESS), to be later sold for a profit when the electricity prices are high. Arbitrage also prevents wasting energy when renewable generation is too high. When generation is too high, it is usually required that this source is turned off, but with the aid of ESSs, this potential energy does not have to go to waste since now this energy can be stored for later use.

These storage systems are generally quite large and commonly have power ratings between 1 - 500 MW. Storage systems performing arbitrage on a daily time scale will generally only charge and discharge 1 or 2 times daily. The size of the storage systems is mainly determined by the application [5].

Electric supply capacity

Energy storage systems can be used to defer the need to invest in new generation capacity or having to buy this capacity on the electric wholesale market. The revenue flows of these capacity-providing systems differ depending on which capacity-related policy is in place. An operation example of this service can be seen in Figure 3.2, where the ESS supplies the peaks, and the ESS charges when the prices are low (for instance, during the night).

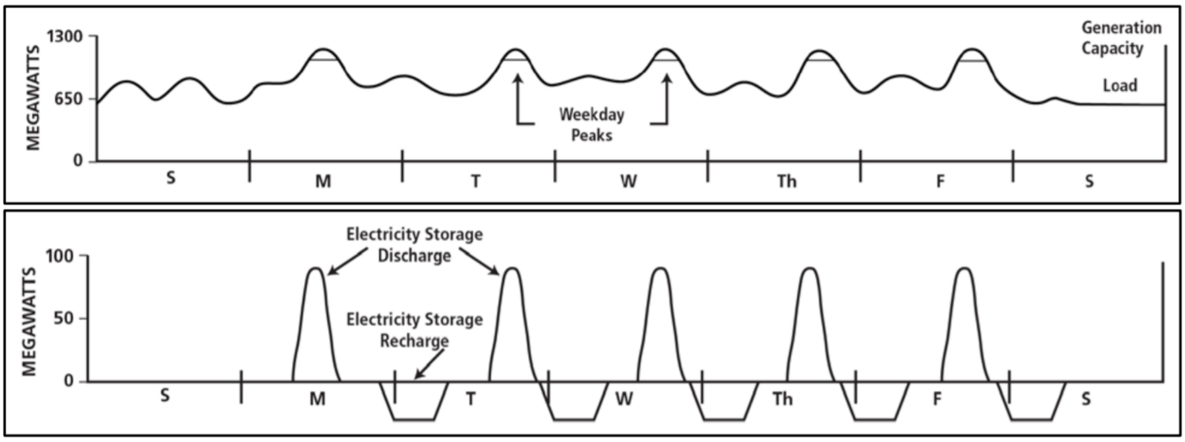

Figure 3.2: An illustration of how capacity supply works (Source:[5])

The service's revenue is mainly determined by the exact implementation of the ESS's operating profile. This operating profile is characterised by the hours of operation, the operation frequency, and the operation duration. This profile is very case specific, depending on the location and the different policies. These policies decide how capacity is priced. This pricing can, for instance, be per hour, allowing for more flexibility. Alternatively, if the capacity has to be available for a specific amount of time, it can make the service less flexible [5].

3.1.2. Ancillary services

Ancillary services are the services that help maintain a reliable grid and ensure sufficient power quality. These services include regulation, reserves, voltage control and black start support.

Regulation

Regulation is managing power flows to match the demand within a control area closely. By regulating, the system frequency remains closer to the nominal grid frequency of 50 or 60 Hz. In the current power system, generating units are responsible for maintaining this frequency by decreasing output if the frequency is too high and increasing if the frequency is too low. However, it is important to note that this regulation can cause faster degradation for large base-load thermal plants. So a primary value of this service can be found in the reduced cost of degradation of conventional generation.

ESS is quite fit to perform regulation. These systems can regulate like conventional generation by reducing output. However, unlike conventional generators, ESSs can also absorb the power in the system, making 1 MW capacity batteries able to do the work of 2 MW generation. This is illustrated in Figure 3.3

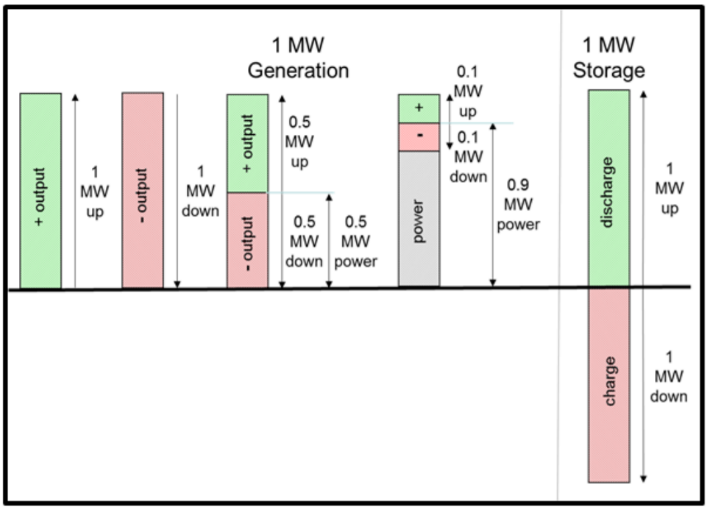

Figure 3.3: An illustration of how regulation by batteries compares to regulation by generators (Source:[5])

In the current implementation of regulation, the storage operator has to pay for storing energy. Therefore, if the efficiency of the ESS is too low, the costs of regulation can be higher than the revenue. These storage systems are in the range of multiple megawatts and are often activated since the yearly cycles can reach up to 10,000 [5].

A study from 2016 [8] describes the regulation service as an required power output that gets negotiated every D units of time.

Currently, an operator will send the regulation signals to the storage regulation unit within reliable bounds, and the storage regulation unit is contractually obliged to follow this signal.

The behaviour of the storage system can be modelled as:

$$SOC(k) = \Gamma SOC(k-1) - \eta_d \delta \left[s_k\right]^+ + \eta_c \delta \left[-s_k\right]^+ \tag{3.1}$$

In this equation, SOC is the state of charge, Γ is the self-discharge rate. η_d and η_c are the discharge and charging efficiencies. s_k is the signal that has to be followed, also known as the automatic generation control signal, and δ is the time unit length.

The 2016 study [8] also compares battery storage with a flywheel storage unit model and argues that using a flywheel for regulation services can be quite economically efficient.

Spinning, non-Spinning and supplemental Reserves

When unexpected influences occur, such as general disturbances and faults, the power supply may become unavailable and that there is an urgent need for additional generation. Since thermal generators have ramping constraints that will not allow for a quick response, ESS can be implemented to stay on standby to provide this fast response. When ESS is used, this storage is always online and ready to provide this reserve, so the number of cycles is minimal since these ESS are only active when reserves are necessary.

Spinning reserve is generation capacity that is always online but not connected to the network. As soon as disturbances occur, this reserve can respond quickly and, therefore, can maintain a stable grid frequency. The study [5] differentiates between spinning reserves, which can respond within 10 minutes and 'frequency responsive' spinning reserves, which can respond within 10 seconds. The response times determine the definition of the reserve type, so whether the reserve is secondary or primary.

Non-spinning reserve can be a block of uninterruptible loads that can be easily disconnected. However, it can also be other non-spinning disconnected generation capacity that can be connected to the grid. This type of reserve needs to be available in 10 minutes.

Supplemental reserve is to aid the initial spinning and non-spinning reserves as a backup. These reserves are initially not synchronised with the grid frequency and only become active after all the other reserves are online [5].

Voltage control
Voltage control is the task of keeping the voltage within certain bounds. The primary way to keep the voltage within normal limits is to provide reactive power. The Dutch TSO Tennet is legally obliged to keep the voltage levels of the grid within certain bounds. The voltage level can be controlled by supplying (inductive) and withdrawing reactive power (capacity) from the grid. The response time of these parties responsible for the reactive power balancing should be able to respond within 15 minutes.

Tennet uses Power Park Modules and generators control to supply this reactive power. However, in the future, when there will be a large amount of ESS in place, it is also possible that the ESS systems can provide these reactive services. Reactive power support is quite location-dependent. For that reason, many distributed storage devices, which will mainly perform other services such as transmission grid upgrade deferral, can be used to provide this reactive power support.

The voltage support for which the TSO is responsible considers the extremely high voltage and high voltage grids (380kV-220kV and 150kV-110kV, respectively). To clarify, the TSO is responsible for contracting parties willing to deliver this voltage support. The current way of controlling these voltage support devices is still being done by telephone, so if there is a need for reactive power, the TSO will phone the geographically optimal facility that should be activated [9] [10].

Black start
When a massive blackout happens and power plants are offline, the entire electricity grid needs a restart. The restart process (a black start) requires quite some steps. ESS can aid this process by energizing transmission lines and giving the generator starting energy [9]. These storage systems are typically in the range of 5 - 50 MW [5].

3.1.3. Transmission and distribution infrastructure services
Infrastructure services are storage services that help prevent upgrading network capacity or aid the energy network by reducing network congestion.

Transmission upgrade deferral
This service is the deferral or sometimes the complete avoidance of transmission system upgrades. This service can be applied on, for instance, power lines that are only overloaded a few times a year. Having to invest in an entirely new power line would be quite expensive. Therefore a cheaper solution is to avoid these small amounts of peaks by investing in a cheap ESS. The size of these transmission-level storage systems is typically between 10 and 100 MW [5].

Transmission congestion relief
Transmission congestion is a situation where available energy cannot be properly delivered to some loads due to inadequate transmission infrastructure. Congestion can lead to situations where the price of electricity has to be locally determined. Therefore ESS can be used to relieve congestion. This congestion relieving can be done by storing energy during low demand and releasing this energy when demand is high, thus avoiding congestion. This type of storage is often placed more downstream in the transmission network. Because then, the storage system is closer to where the electricity is needed [5].

Distribution upgrade deferral (and Voltage Support)
Similar to transmission grid upgrade deferral 3.1.3, the function of distribution grid upgrade deferral is to delay/avoid investing in distribution infrastructure by implementing ESS. The main difference is found in the size of the storage system and the voltage levels for which it operates. These energy storage systems are generally a lot smaller in size and can be between 500 kW and 10 MW.

These storage systems that enable distribution gird upgrade deferral are also especially fit to perform voltage support on distribution level and can be an essential income stream for these systems [5].

3.1.4. Customer energy management services

Customer energy management services are downstream of the energy network and can be executed by relatively small storage systems. Services provide power quality and reliability, and there are also services with financial incentives like demand charge management and retail electric energy time shift. These services will be further discussed in this subsection.

Power quality

Providing excellent power quality is important for consumers since when the power is of such poor quality, it can induce unwanted effects for several loads and even cause significant damage. When ESS operators try to maintain good power quality, they are responsible for the following:

- To reduce unwanted deviations in voltage magnitude, these can include, for instance, voltage spikes or sags.
- To keep the frequency around the rated frequency of 50/60Hz.
- Ensuring the power factor remains close to 1.
- To limit unwanted harmonics in the grid.
- If the grid connection is weak, power quality also includes preventing small interruptions in service (several seconds).

Since most of these power quality services last a few seconds to minutes, the battery storage capacity does not have to be that large [5].

Power reliability

When there is a blackout, or consumers get disconnected from the grid, a local storage system can help consumers maintain access to electricity. These storage systems can be privately owned by the electricity customer or by a larger ESS company [5].

Retail electric energy time-shift

Retail electric energy time-shift is essentially the same idea as normal energy time-shift. However, this service is done by the end-users. With the main objective to reduce their electricity costs, these local storage units charge when the price of electricity is low and discharge when the price is high. However, the actual real-time electricity prices are unknown to the energy storage owner, so the price of electricity is generally determined by the contract with the retailer. In the 2013 study [5], they discuss a hypothetical price profile that changes during the hours of the day. Such that the price of electricity is 32 cents/kW between 12.00 - 18.00 and, for instance, 10 cents/kW between 21.30 - 8.30. In this scenario, it is possible to do retail with a single system [5].

Demand charge management

Demand charge management is the prevention of load peaks.

When there are monthly peaks in the demand profile of a consumer, they can be charged for these demand maximums [11].

In demand charge management, a consumer can dampen these peaks with the help of ESS, thus reducing the electricity bill. For more prominent industries, some peaks can be damped to prevent demand charge penalties.

3.1.5. Combining storage applications into one model

Reviewing the different storage system applications discussed in this chapter and from Figure 3.1, it can be seen that some services have quite similar means of modelling them, the only difference is found in scale and location within the electricity grid. This thesis argues that the entire list of storage system applications can be modelled using three basic grid services. These are Arbitrage, Peak Shaving/Load levelling and Power Quality. Figure 3.1 shows that the services are sorted into different colours, red for arbitrage, green for power quality, and blue for peak-shaving.

Peak shaving
Peak shaving and or Load levelling encompasses the following services:

- Electric supply capacity
- Transmission & distribution upgrade deferral
- Transmission congestion relief
- Demand charge management

All these services have in common that they have an obligation to reduce, shave or keep the load level under a certain constant level. The main difference between these services is the topological location. For instance, electric supply capacity is entirely upstream in the electricity grid, and demand charge management is completely downstream in the network.

Arbitrage
Arbitrage describes two services:

- Electric energy time shift
- Retail electric energy time shift

Both of these services have one main goal, profit maximization. The only difference is the location in the electricity network, as electric energy time shift is considered to be a bulk time of energy storage and generally located more upstream in the network. Retail electric energy time shift is downstream of the electricity network. Since the goal is the same, the modelling of both services can also be done similarly. It should be noted that arbitrage performed by storage systems with no self-discharge can lead to peak shaving behaviour, but there is an essential difference between these two. Peak shaving systems are obligated to remove the peaks, and arbitrage systems only shave peaks if they are economically viable.

Power quality
Power quality services describes the following services:

- Regulation
- Spinning, non-spinning and supplemental reserves
- Voltage Support
- Black start
- Power reliability
- Power quality

These services have one thing in common: and that is that their activation is predominantly random. Except for voltage support, all these services require storage systems to recharge randomly at different frequencies. To exemplify, the black start is rarely used, but it cannot be predicted when this service should be activated. After activation, this storage system should be recharged. Similarly, regulation is frequently activated throughout the day depending on the regulation demand, which is random. The storage system has to recharge or discharge randomly. The only differences between these services are the activation frequency and the operation size. Since these systems still intend to save on recharge costs, the storage systems will wait for optimal electricity prices to do the charging/discharging, and this will again lead to peak shave-like behaviour. However, it should be stressed that the main difference between power quality peak shaving and other types of peak shaving is that this behaviour is activated due to primarily random events.

To summarize, arbitrage is for storage systems to shave peaks to maximize profits, peak shaving is for storage systems to shave peaks out of obligation, and power quality results in the random necessity to shave peaks. Note that although this is not the most accurate representation of these different services, it does allow for a simple generalization.

3.2. Energy storage systems and technologies

This part of the literature study focuses on the different methods to store electrical energy and takes a closer look into categorising these different technologies. Categorising energy storage systems will be done by looking into the specific technology on which the technology is based. However, categorisation can also be done based on the different applications these storage system technologies can provide to the grid.

3.2.1. Overview of energy storage technologies

Multiple studies [12], [13] categorize the storage technologies into four main groups. The first group is chemical storage, which comprises storage devices such as conventional batteries, flow batteries and hydrogen storage. So essentially, all storage methods that require chemical reactions to access stored energy. Electromagnetic energy storage systems are the second group of storage technologies comprising electric field storage systems such as supercapacitors and magnetic field storage systems such as superconducting magnetic energy storage (SMES). There is also the thermodynamic energy storage group which considers storing energy using pressure or heat. Mechanical energy storage is the last group of storage technologies. A form of mechanical storage is gravity, which is applied in pumped hydro storage technologies and another form of mechanical storage is kinetic storage which is implemented using flywheels. These different storage technologies are visualised in Figure 3.4.

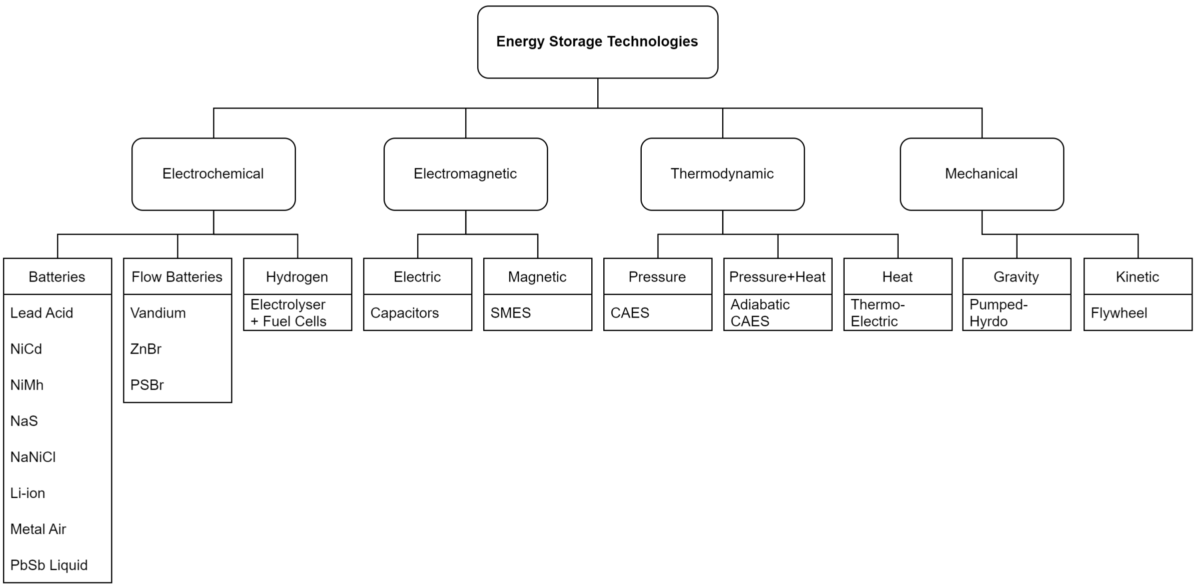

Figure 3.4: Overview of energy storage technologies (Adapted from:[12])

3.2.2. Electrochemical storage

Electrochemical storage technologies are technologies which store energy using chemical bonds. This group exists out of batteries, flow batteries and hydrogen storage systems. These chemical storage technologies will be further explained in the following subsections.

Battery storage

The first group of chemical storage technologies are batteries. Battery storage technology can be an essential component in solving the energy storage need and can provide a wide variety of grid services [5][14].

Li-ion batteries are already commonly used in small to medium appliances, like phones, laptops and electric vehicles. But also within the electricity grid, Li-ion technology can be a significant ancillary service contributor since it can be used for smaller time scale applications like frequency regulation and larger time scales like daily arbitrage and transmission/distribution grid upgrade deferral.

Li-ion has no place in long-term storage, for which energy needs to be stored for more extended periods (weeks/months), and this is also the case for other battery technologies. This is due to the self-discharge rates of all these battery technologies [12][13][14].

Li-ion technology is itself an overarching term for the different types of ions that can be used to make these batteries. These ions can be, for instance, cobalt and manganese. Choosing the right Li-ion technology is vital since different ions will result in different battery parameters. To give an example: the power density of Li-manganese is in the range of 1800W/kg, while the power density of Li-cobalt is around 760W/kg.

When comparing Li-ion-based batteries to other battery technology, it can be concluded that Li-ion has the most promising parameters since Li-ion has a lower self-discharge rate, higher round trip efficiency and higher energy density. A downside of Li-ion technology is the higher capital costs, as these are 1200-4000 $/kW and 100-2500 $/kWh, which is higher than other technologies [15].

Lead acid battery technology has one main advantage over other storage technologies, namely that it has the lowest costs per kWh, at around 150 $/kWh.

However, lead-acid batteries have quite some considerable downsides. Some of these are listed below:

- These batteries require toxic materials to produce and, therefore, can have a large negative environmental impact.
- Both energy and power density are quite low, namely 180 W/kg and 60-75 Wh/L [14].
- The maintenance costs and requirements of these batteries are high.
- The lower power density leads to high material requirements, and therefore the battery storage system will take more physical space [15].
- Lead-acid batteries have a lower round trip efficiency (around 85%).
- Lead-acid batteries have a high self-discharge rate (around %/day 0.17).

These factors result in the lead-acid battery having a more limited application range since it can generally store energy for a shorter time duration than li-ion. This limitation means it has to operate on shorter time scales (hours/days). Therefore, lead acid's primary use in the electricity grid will mainly be for power quality and frequency stability. However, some more advanced lead acid technologies can also have a role in transmission and distribution grid support services [14].

nickel-metal hydride battery storage systems are relatively cheap (250 $/kWh) and safe storage technology. However, due to some negative characteristics like the fast discharge rate, the low output voltage and the memory effect (which causes these batteries to hold less charge). It is seen that this mature technology is slowly being replaced by other types of battery technology [14]. Due to this fast discharge rate which is between minutes and seconds at rated power [12], these batteries only operate in the grid for frequency stability, power quality, and grid support. The volumetric energy and power density are comparable to the Li-ion battery, namely 140-300 Wh/L and 250-1000 W/kg, respectively.

Overview of parameters related to optimization A study from 2017 [16] discusses some other important parameters that apply more directly to optimization problems and modelling. These can be seen in the table below:

Parameter		Unit	PbA	LFP	NMC
η_{BAT}	Round trip efficiency	%	85	98	95
SD_{BAT}	Self-discharge rate	%/day	0.17	0.02	0.02
$LifeTime^{80\%}$	Life time	Years	10	15	13
$LifeCyc^{80\%}$	Cycle life indicator	FEC	1500	10000	4500
SOC_{min}/SOC_{max}	Usable SOC	%	50-100	5-95	5-95
C_{var}	Variable battery price	€/kWh	271	752	982
C_{fix}	Fixed total price for storage	€	medium	high	low

Table 3.1: Overview of optimization parameters for different battery storage technologies (LbA: Lithium acid, LPF: lithium-iron-phosphate, NMC: lithium-nickel-manganese-cobalt)(Source:[16])

In this table, FEC indicates the Full Equivalent Cycles, the number of complete cycles a battery can do. Notice that this table does not cover the same lithium-ion batteries discussed before. However, the primary purpose of this table is to give the reader some valuable parameters to use. As can be seen, some other vital parameters regarding battery modelling are the variable operation costs, lifetime and cyclic ageing. Where cyclic ageing is a negative effect that reduces the battery's lifetime, cyclic ageing is directly correlated to the frequency of operation and depth of discharge when operating.

Flow batteries
Another type of chemical storage is the flow battery. Three commonly used flow batteries are vanadium redox, poly sulphide Bromide and zinc bromide. Since vanadium is the most mature technology among these technologies, this type will be used for the analysis.

The vanadium redox flow battery (VR) is based on the chemical reaction between two different vanadium-based electrolytes. These electrolytes are stored in two tanks a positive tank (containing, for instance, V^{5+}/V^{4+}) and a negative tank (containing, for instance, V^{3+}/V^{2+}). These solutions get pumped through the cell stack, which is the place where the reaction takes place. These solutions enter the cell stack but are separated by a small membrane that only allows ions to pass. When the battery is completely discharged, the negative tank consists of only V^{3+} ions, and the positive tank only has V^{4+}. Once an external source starts charging the battery, ions start moving through the membrane and balance the overall charge, the V^{3+} solution starts accepting electrons and the V^{4+} is giving electrons away. This movement is a result of the externally applied voltage. In the fully charged battery, the V^{3+} ions are replaced by V^{2+} ions, and the V^{4+} ions are replaced by V^{5+} ions. When the battery is discharging, the opposite takes place. With the VR battery, it is conceptually simple to increase the storage capacity by increasing the size of the tanks. Similarly, if the maximum power output needs to be increased, the number of cell stacks can be increased.

An advantage of the flow battery is that the discharge rate is negligible, which allows for longer-term storage capabilities. So in the future, the VR batteries can do longer-term operations within the grid, such as larger power grid balancing and bulk power storage. A large disadvantage of this type of storage is the low power and energy density, meaning that the size of such a system needs to be quite large for a large storage capacity. Another disadvantage is that the technology is quite novel, meaning that the technology currently needs more research and development [17][18].

A study from 2018 [19] evaluates different redox flow batteries and gives some operational parameters. Some of these parameters that significantly influence optimization-based modelling have been summarised in table 3.2.

Parameter	Unit	Redox Flow Battery
Round trip efficiency	%	65-75
Self-discharge	%/day	neglectable
Calendric life time	Years	>10
Cycle life indicator	FEC	>10000
Usable SOC	%	5-95
Response Time	ms	10-20

Table 3.2: Overview of general redox flow battery parameters (Source:[19])

Hydrogen energy storage
The last group of chemical storage systems is hydrogen energy storage. This type of storage is still in a developing stage but remains to be a promising technology.

There are multiple ways to generate hydrogen, but when it comes to storing it from excess electricity, electrolysis is the best option. This is because this method does not require fossil fuels (other methods of creating hydrogen include steam reactions with methane and or extraction from fossil fuels). Electrolysers currently have efficiencies ranging from 40% to 80% [20].
A study from 2012 [21] compares different energy storage systems and briefly discusses hydrogen fuel cells. Here a round trip efficiency of 20-50% is given. Some drawbacks of hydrogen energy storage can be found in the high capital costs and that this type of technology still needs much development. Nevertheless, due to the low self-discharge rates, this chemical storage technology could be used for longer-term storage applications.

3.2.3. Electromagnetic magnetic energy storage

This energy storage technology is based around storing energy in electric and magnetic fields. In this section, some examples of this type of storage are discussed. These storage technologies are superconducting magnetic energy storage (SMES) and supercapacitors.

Super Capacitors
The supercapacitors store their energy in the form of an electric field between two plates. Where the total energy stored in the capacitor can be found by:

$$E = \frac{1}{2}CV^2 = \frac{1}{2}\frac{A}{d}\varepsilon_r\varepsilon_0 V^2 \tag{3.2}$$

Here is V the voltage, C the capacitance, A the surface of the plates, and d the distance between the two plates. And ε_r and ε_0 the relative permittivity and permittivity of free space respectively.

The application of supercapacitors is found in their ability to charge and discharge their energy quickly. Also, the lifetime of supercapacitors is around 10^6 cycles, which is large relative to battery storage technologies. However, a disadvantage of these devices is the costs, since these can range between 12.960-28.000$/kWh. The high costs are why this technology is generally only applied in smaller-scale applications and will likely not play a significant role in large-scale grid applications [17].

Many other concrete parameters can be found in a study from 2012 [21]. Some functional modelling parameters, such as the energy efficiency, are also given, which is between 90% and 95%. Furthermore, the supercapacitor has the highest self-discharge rate among the other storage options, around 20% to 40% per day.

Superconducting magnetic energy storage
The SMES stores its energy in a magnetic field, quite similar to the supercapacitor. This magnetic field is created by running current through a coil made of superconducting material, where more conductivity means less energy loss. The total stored energy can be found by:

$$E_L = \frac{1}{2}LI^2 \tag{3.3}$$

Here L is the inductance of the coil, and I the current that passes through the coil.
Unlike supercapacitors, literature believes there is a future for SMES in large grid applications. This is mainly because of its high power capacity, stability, fast response time, and ability to discharge and charge quickly. Also, the efficiency of the SMES is high (95%). There are significant challenges for practical SMES application, mainly because the SMES requires a lot of cooling for the coil to remain superconductive. The materials are quite expensive, and the technology is expensive to operate. Also, due to the fast discharge rate, the SMES has a limited use case in the electricity grid, namely for short but larger power applications. There is still a lot of commercialization and research necessary before this technology will be applied on larger scales [12][17].

In the study [21], some extra challenges are discussed when implementing SMES, and operational parameters are given. Most notable are the high energy efficiency of 95-98%, low energy density 0.5-5 Wh/kg and a relatively fast discharge rate of 10-15% per day. The system does not suffer a lot from cycle degradation since it can cycle its charge more than 100.000 times, which is a large improvement compared to battery technology.

3.2.4. Thermodynamic storage

Thermodynamic storage comprised thermal energy storage (TES) and compressed air energy storage (CAES). These storage devices are all based on thermodynamics, like temperature differences and differences in pressure. In the next section, the primary function of CAES will be discussed, and its applications in the electricity grid will be covered.

Compressed air energy storage

CAES is the practice of storing energy in the form of compressed air. This storage system can store low-priced electricity by using electric compressors, compressing the air into a storage tank. The storage tank can be of any type. Larger CAES systems can use naturally existing structures like salt caverns to store the compressed air. It is also an option to store compressed air in manufactured storage tanks.

The discharging of CAES systems is done by the expansion of the air, which are channelled through turbines. When the expansion of air happens, the temperature can drop significantly, which can cause condensation and freezing of machinery. Therefore CAES requires ways to deal with this problem. There a multiple classifications of CAES systems, and each classification deals differently with the heat problem. For instance, Diabatic-CAES systems use an external heating source to heat the expanding air. Other solutions include adding gas to the air or using cool air in TES systems.

CAES's power capital costs are between 400-2250 $/kW, and the energy capital costs are between 1-140$/kWh. Energy efficiencies of these systems are between 70% and 89%, and self-discharge rates are low.

The storage capacity is quite large and comparable to pumped hydro storage. This type of storage is ideal for energy management applications and longer-term storage since these systems can be scaled up to hundreds of megawatts. CEAS systems can also be used for other grid applications like some ancillary services, such as voltage control and frequency regulation.

Some disadvantages are the lack of experience and geographical dependency. Since there are currently not that many CAES systems installed, this type of technology is very much in development, which means the capital costs of these systems can be high. Also, CAES requires the presence of underground cave systems where this air can be stored, and these can be difficult to find [13][17][21][22].

3.2.5. Mechanical storage

Mechanical energy storage is storing energy by storing it as kinetic/gravitational energy, such as in flywheels and pumped hydro storage.

Flywheel storage

Flywheel energy storage devices store their energy in rotational energy. The amount of energy stored is based on the shape of the wheel, the mass and rotational speed. The energy stored in the system is found by:

$$E = \frac{1}{2}J\omega^2 \tag{3.4}$$

The flywheel is build-up of the following components: An electrical machine, generally a permanent magnet synchronous machine, rotor bearings, power converters and a containment chamber.
The flywheel is generally used for power quality applications and frequency stability. The energy costs for low-end flywheels are between 200 and 300 $/kWh, and for high-end high-speed flywheels, 25,000 $/kWh. Power capital costs are between 30.28-700.00 $/kW.
The main advantages of the flywheel are that it has a long lifespan, lower maintenance compared to other storage devices and a low environmental impact [13][17][23].

Flywheels are relatively efficient, having efficiencies in the range of 93%-95%. The self-discharge rate is very high since it completely discharges itself in one day (100%/day) [21].

Pumped hydro storage
This type of storage requires two bodies of water which have different elevation levels from each other. The storage is based on storing energy in the form of gravitational energy. When there is, for instance, excess electricity and when the price is low, water will be pumped to the upper reservoir. When energy is required, the water can flow to the lower reservoir again, and electricity can be generated. Since the energy is stored based on gravitational energy, the system's capacity is based on the mass of the smallest reservoir and the height difference [12].

The application range of pumped hydro storage has been improving over the years. Usually, the pumped hydro storage was used for just bulk storage and energy management since these pumped hydro energy storage systems can be up to multiple gigawatts. However, due to the introduction of variable speed machines, the pumped hydro storage facilities now also be used for smaller time-scale applications like frequency regulation, where ramping plays an important role [17].

The power capital costs of the system ranges between 300 $/kW and 5,880 $/kW. Energy costs are relatively low, namely between 1.00-291.20 $/kW. The system's lifespan is between 20 and 80 years, making it compared to battery storage significantly more durable [24]. The energy efficiency of this system is 75%-85%, and the self-discharge rate is very low and can generally be neglected [21].

If it is geographically possible to implement a pumped hydro storage facility, then it is a great storage option. It should be taken into account that the energy density is relatively low 0.5-1.33 kWh/m^3. The energy density implies that implementing such a system requires quite a lot of volume.

3.2.6. Summary of storage technologies

The analysis of the different storage technologies has led to the insight that most storage systems can be modelled using a similar set of constraints and or modelling considerations. The importance of these modelling constraints is highly dependent on the specific application of the storage model. However, some constraints prove to be more common than others. The most essential parameters to consider when modelling energy storage systems are the power rating and energy storage capacity. The sizing of the battery greatly impacts where the system can be most optimally implemented in the electricity network. An illustration of this concept can be seen in Figure 3.5.

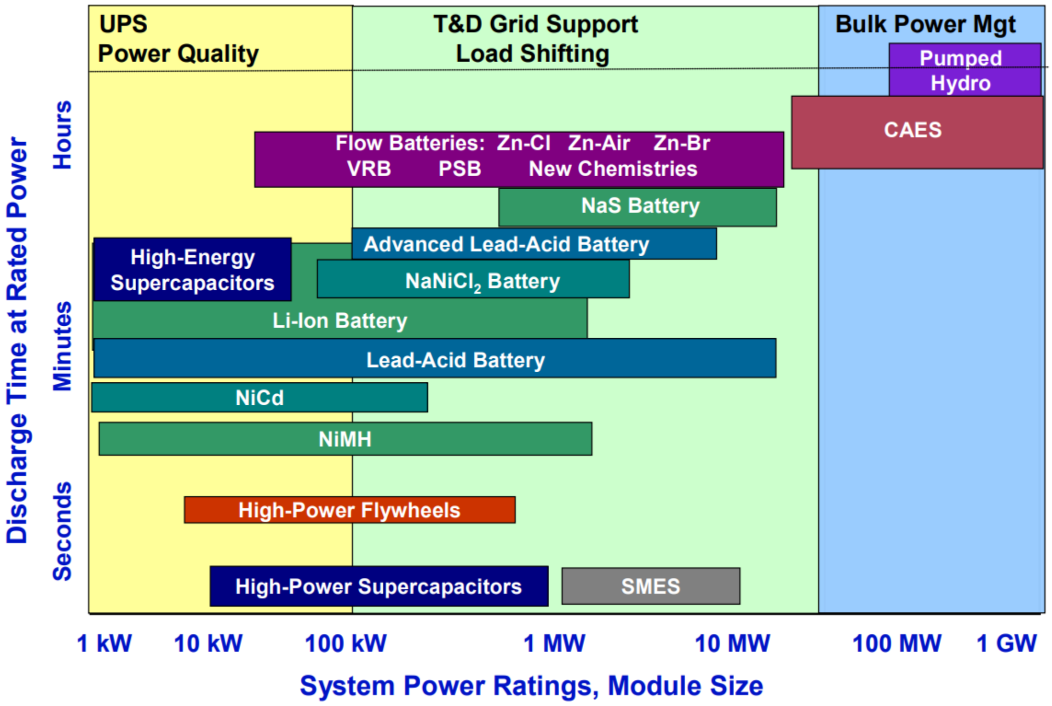

Figure 3.5: Storage Systems applications based on power rating and storage capacity (Source:[5])

The figure gives an overview of storage technologies and information regarding the application of some of these.

Other parameters that influence the application range of energy storage systems are:

- Charging efficiency
- Discharging efficiency
- Self-discharge

The charging and discharging efficiency determine how much of the energy extracted from the network can be effectively used again at a later time. These charging and discharging efficiencies are generally determined by the physical process of the storage system, and the power conversion system implemented. The self-discharge rate is another important parameter to take into consideration since this parameter will determine the time scale at which the storage system can operate. Storage systems with a large self-discharge rate are unfit to perform arbitrage. Based on the energy storage technology and purpose of the model, some storage constraints that should be considered are listed below:

- The discharge and charge ramping rate
- The discharge power and charging power
- The efficiency of charging and discharging
- The self-discharge rate
- The cyclic ageing
- The calendrical ageing
- The optimal state of charge and operating range

To elaborate on this list, cyclic ageing is mainly a battery storage-related problem where the system's lifetime reduces based on the depth of discharge. In contrast, calendrical ageing has limited to no impact on other storage technologies. Similarly, the ramping rate of the battery systems is relatively high and can, therefore, sometimes be neglected, while for pumped hydro storage, this should be considered. When it comes to modelling, the selection of constraints mainly depends on the model's goal and implemented energy storage technology.

4

Electricity Markets for Storage Systems

In the previous chapter, all of the storage-related grid services were briefly discussed. This chapter will answer the question of where and how the storage systems will be compensated for providing these services. This will be done by analysing the European markets from which simplified market models can be made.

4.1. Markets overview

The energy markets in Europe are built up of two major components, the balancing market and the wholesale market, an overview of these markets can be seen in Figure 4.1. All these markets have one primary objective: to match generation with demand while keeping the total system costs as low as possible. The wholesale market consists of the day-ahead market (DAM) and the intra-day market. The day-ahead market is compared to the balancing market not that precise. Here generation units will be cleared on an hourly scale the day before the operation. Since this hourly resolution does not result in exact matching between demand and generation, and since this clearing is based on forecasts, there is generally a substantial mismatch between generation and demand. To reduce this mismatch, there is an intra-day market, which clears N-hours before actual operation and has a 15-minute resolution.

The balancing market is responsible for keeping generation and demand the same in real time. This done by contracting generation units that are able to provide balancing/reserve power. There are quite some different reserve types, which differentiate from each other by market size, timescale and frequency of reserve activation [25].

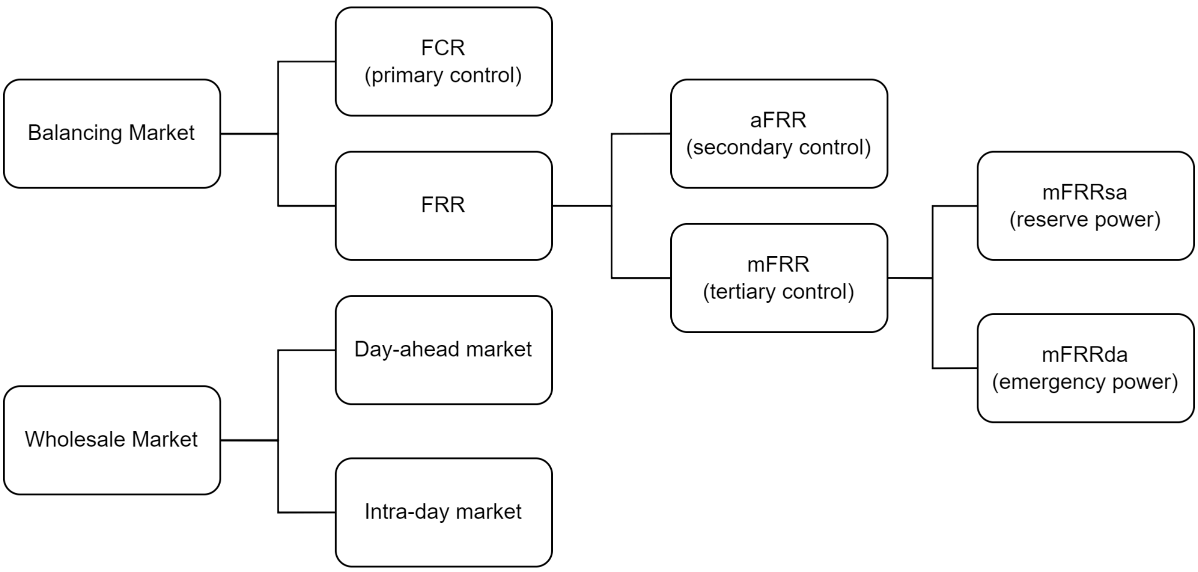

Figure 4.1: Overview of the energy markets (Adapted from:[25])

4.2. Wholesale Markets

The wholesale markets include the day-ahead and intraday market.

4.2.1. Day-ahead market

The day-ahead market (DAM) is where most of the energy is being traded. This market is cleared daily with an hourly resolution. Market clearing is the process of matching generation and forecasted demand to minimise the total system costs. Generators can place bids on the market. In healthy markets where there is a situation of perfect competition, all the generators will bid marginally. When the market is cleared, and demand and generation are matched, the electricity price is generally set equal to the price of the most expensive active generator. The marginal revenue of the generators can then be determined by subtracting the marginal costs per MWh from the electricity price [26].

4.2.2. Intraday market

Since the DAM is based on daily forecasts and uses an hourly bidding profile, the actual real-time demand differs. To solve this difference in generation and demand, the intraday market is introduced, which is cleared during the operation day. This market trades over the differences between the more recent forecast and the day-ahead forecast. This market is cleared with a 15-minute resolution, which still means that there is still a mismatch between generation and demand. The balancing markets will resolve this mismatch.

Congestion management with GOPACS

GOPACS is an initiative by Dutch system operators with the objective of reducing congestion. GOPACS is especially interesting for grid users with flexible generation or demand; therefore, this is also interesting for storage systems. So essentially, what GOPACS enables is the compensation of congestion management services. GOPACS operates in the intraday market and is not a market platform itself. Participating market parties can provide buy and sell orders, for which GOPACS checks if it solves congestion and does not create congestion anywhere else. If these requirements are met, the buy-and-sell orders are matched, keeping the grid balanced and reducing congestion. If there is a mismatch between the buy and sell order prices, then the grid operators will compensate for this difference (also called the spread) [27]. For storage system owners, GOPACS enables a source of income when performing congestion management (providing peak-shaving services).

4.3. Balancing Markets

The balancing market is subdivided into frequency containment reserves (FCR) and frequency restoration reserves (FRR). The FRR is then further divided into automatic frequency restoration reserves (aFRR) and manual frequency restoration reserves (mFRR). These reserve types will be further explained in this section.

4.3.1. Frequency containment reserves (FCR)

Frequency containment reserves (FCR) are responsible for stabilizing the frequency for high voltage grids. In the Netherlands, FCR should be able to keep the ratio between frequency change and power change constant in less than 30 seconds. This is done automatically by the primary control of a generating unit. In the Netherlands, the TSO is responsible for providing the FCR. The volume of FCR that Tennet has to provide is at least 116 MW in 2022. The FCR volume that has to be available is determined annually by the ENTSO-e, a European association for the cooperation of TSO's. In 2022 the partial FCR production is set to be 3,867%, meaning that for a reference incident of 3000 MW, the dutch TSO has to provide 116 MW [9].

4.3.2. Automatic frequency restoration reserves (aFRR)

According to Tennet [9]: "aFRR is responsible for maintaining the real-time power balance of the Netherlands". And in that regard aFRR is similar to the regulation discussed in 3.1.2. In the Netherlands, the minimum contracted aFRR capacity must be around 290-420 MW, both upwards and downwards. A rule for generators providing aFFR is that the amount of reserve contracted needs to be activated within 5 minutes after a request is made. These constraints lead to thermal generators only being able to provide a set amount of aFRR capacity based on their ramp rate. To elaborate, upwards regulation is when a balance service provider (BSP) is tasked to increase power output and increase power inserted into the network. And downwards regulation is when the BSP is tasked to reduce output power and decrease the power input into the system. It is also possible to increase the load with downwards regulation. Storage systems can increase the load by charging.

With upwards regulation, the TSO will request an amount of extra power to be inserted into the grid to the balance responsible party (BRP) or BSP. The TSO will pay the BRP/BSP by the amount of extra energy the BSP has to insert into the network. For downwards regulation, the BSP/BRP is requested to output less power. Therefore the BSP saves energy and has to pay the TSO [26]. Regulation bids have two bidding systems, one for the reserved capacity (euro/MW) and one for the energy (euro/MWh). The latter bidding ladder is seen in Figure 4.2.

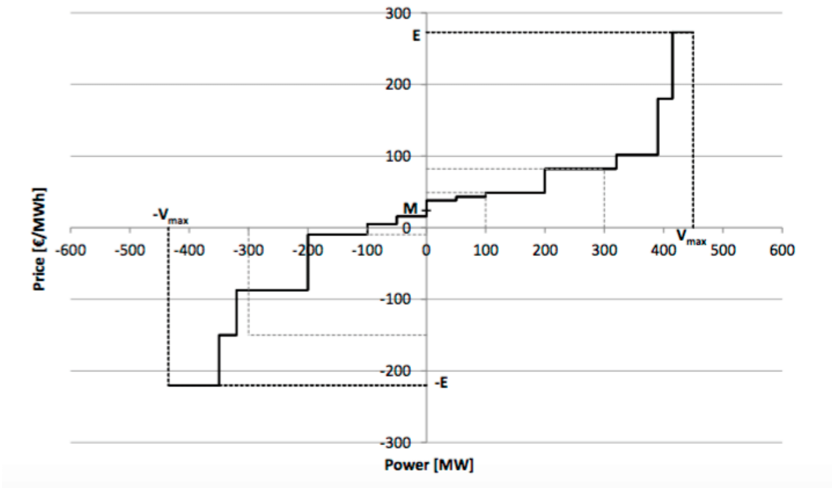

Figure 4.2: Theoretical bidding ladder for energy regulation (Figure taken from:[28])

For energy storage systems, this concept is more straightforward to explain since, for upwards regulation, the system is discharging and therefore wants to be compensated for the lost energy. Therefore the TSO pays the storage system. And when the storage system is charging/down regulating, the storage system owner has to pay the TSO for the energy.

4.3.3. Manual frequency restoration reserve (mFRR)

mFRR consists of reserve power (mFRRsa), and emergency power (mFRRda). These reserves are quite similar to aFRR. However, mFRR is specifically used for longer-lasting power deviations. The amount of contracted upwards and downwards mFRR capacity changes every half year and is set for 995 MW upwards and 835 MW downwards in 2022 Q1-2 [9].

4.4. Balancing market theory

A paper from 2014 [29] provides a general guide to the balancing market, which explains some of the theoretical balancing mechanisms of the German balancing market. In this section, the main takeaways are covered.

There are quite some constraints for general thermal units to provide balancing power. Namely, the amount of aFRR a unit can provide depends on the load gradient in $[MW/min]$ and activation time in $[min]$. So this implies that when the load gradient is 30 MW, the BSP can provide 5*30 MW = 150 MW aFRR. The ramping rate for aFRR demanded by Tennet is given by: Tennet, and is currently 7%, but as of 01-07-2022 this rate will be changed to 20% per minute. This means that BSPs should provide the full power within 5 minutes instead of approximately 15 minutes. Another constraint for the BSP is that the reserve bid should be smaller than the difference between the maximum and minimum output.

There can be two case scenarios regarding the capacity costs of balancing power. There are inframarginal power plants, which have variable costs below the predicted DAM price. And there are extra-marginal power plants which have variable costs higher than the DAM price within the respective bidding time. Inframarginal units have capacity costs equal to the DAM market price minus the variable costs. For extramarginal power units, the valuation for reserves is a bit more complex. These units are obliged to operate at their minimal capacity in order to participate. This makes their capacity costs dependent on the difference between variable costs and the DAM electricity price and on their minimum operation level and balancing power participation. To summarize the capacity costs for positive power regulation are given by 4.1.

$$CC^{Reserve} = \begin{cases} (MC - \lambda^{dam}) * \frac{CAP^{min}}{CAP^{Reserve}} & \text{if } MC > \lambda^{dam} \\ \lambda^{dam} - MC & \text{if } MC \leq \lambda^{dam} \end{cases} \tag{4.1}$$

Here is λ^{dam} the DAM price, CAP^{min} the minimum operation level, MC is the marginal costs, and $CAP^{Reserve}$ is the capacity allocated by the generator for the reserve. When using this equation and bidding according to this method, there can be a problem, namely that the generators can potentially bid a marginal capacity price and then bid their energy costs to something really high. TSOs have different methods of solving this issue. One method is by adding a $h * MC$ factor to the capacity clearing process, for which h is a parameter between 0 and 1, representing the probability that the reserve will be activated. So then the TSO will clear based on the capacity costs plus the probable costs of having to activate: $CC^{Reserve} + h * MC$.

4.5. Market suitability for battery systems

In a publication by DNV [25], a summary of battery systems' suitability for multiple markets is made. Here the main conclusions were that storage systems were very fit to participate in the FCR market, and therefore FCR should always be considered when it comes to investment models.

aFRR is also a good market to participate in as a storage system. For aFRR however, there can be extended periods of only upwards or downwards regulation, which causes storage systems to discharge fully. Therefore these energy storage limitations may induce challenges regarding contractually agreed aFRR delivery obligations.

mFRRsa and mFRRda are quite unattractive markets for battery systems. This is mainly because of the capacity and energy batteries have to reserve for operation. When these reserves are activated, it can be for quite a long time. Therefore batteries need to have a lot of charge reserved. The activation frequency of these reserves is less than 1% of all PTU's. For these reasons, mFRR is an unattractive market for batteries.

The intraday market is also an attractive market for battery storage systems, since it allows for more real-time optimization. The Day-ahead market is less attractive. A contributor to the poor performance could be the battery's high operating costs due to the significant cycle depth causing reduced lifetime, which makes other markets more profitable.

An important thing to notice is that this market suitability analysis has been done for typical battery storage systems, excluding flow batteries. So to clarify, this publication did not consider other storage technologies like flow batteries or pumped hydro, for which the DAM and aFRR market could be more profitable.

4.6. Design Options

The overall design of all these markets can be quite detailed, but when it comes to a general storage model participating in European markets, a general design proves difficult. This is mainly because every European TSO has different rules and definitions for different markets. This section will look into these differences and also in different ways on how these markets can be modelled.

4.6.1. Wholesale market design options

The wholesale market is used as an overhauling term for the day-ahead market and the intraday market. So when it comes to simulating this market, there are different options. One is to neglect the intraday market and to simulate only the DAM as an optimisation problem with an hourly resolution. The other way is to include the intraday market fully and implement it as a two-stage process, where the hourly DAM will be cleared and then the deltas on the intraday market. The third option is to clear them both simultaneously by simulating the unit clearing on a 15-minute interval.

The optimization interval can also be chosen. It is possible to optimize every 24 hours or each hour, assuming that the optimization horizon is the same. Optimizing every 24 hours over every hour is significantly faster, and this is especially the case for long-term simulations. However, by optimizing every hour, the storage system can better adapt to forecast errors and balance market influences.

It is also possible to model the wholesale clearing process by matching demand en generation by repositioning the demand each time step on the merit order curve. The advantage is that now the simulation can be much faster than when solving this using optimization. A downside is that the optimal behaviour of the storage system is much harder to represent since this system requires a separate entity to keep track of the optimal storage behaviour and ensure that the storage system remains within bounds.

4.6.2. FCR design options

Modelling FCR is inherently different from FRR. This is because FCR responds to a measurable frequency change in the electricity grid, while FRR responds to a control signal based on the area control error. Also, FCR does not have separate upwards and downwards bidding since the capacity bid on these markets is for both upwards and downwards frequency regulation.

The German market has already given a few requirements for storage system participation. Namely, it is possible to join the German FCR market if the system can comply with the following requirements (from [30]):

- Measurement of frequency within 10 mHz
- Proportionally accurate power activation
- When the deviation is larger than 0.2Hz, the system needs to be fully activated.
- The full FCR needs to be active within 30 seconds.
- The ESS needs to be able to provide this capacity for a full 15 minutes.
- And the ESS needs to be always available.

So when designing an FCR market, it should be noted that the requirements and definitions remain similar to the German design.

4.6.3. aFRR design options

Creating a general model of the European aFRR market proves challenging because the rules and definitions differ across countries. A document by Entsoe [31], addresses the differences in aFRR rules and mechanisms between European TSOs.

One of the differences between European TSOs that directly input the capacity generators can allocate to aFRR, is the full activation time (FAT). Which is the time for which the generator needs to be able to fulfil the aFRR request, and this time is dependent on the size and ramping rate of the generator. For illustration, if the FAT is 5 minutes, then a 100 MW coal generator with a 30%/15min ramping rate can only provide a maximum of 10 MW aFRR capacity.

Also, there are different ways of activating aFRR. These are in merit order and pro-rata. aFRR energy clearing using merit order minimises the overall energy costs by activating the cheapest aFRR providers first, similar to how it is done in the DAM. When using a Pro-rata market energy clearing process, all the generators receive the same delta control signal. Therefore the energy that has to be cleared by each generator is scaled based on the bid size of the generator.

Another difference is the control cycle, which is the time between the calculation of the aFRR request and the submission of the request.

Also, the bidding scope of the generator is a significant difference. This has to do with two things. One is the frequency for which the BSP/BRP can submit a bid. This can be every 24 hours, but also every 4 hours like in Germany [32]. For storage applications, a higher bidding frequency can lead to more profitable operation since the storage system can provide more capacity and has more opportunities to adjust the maximum capacity the system can provide based on the state of charge. Secondly, the bid can have different resolutions. This means that generators still submit bids every N hours but can define the bid every 15 minutes or every hour, for instance.

The market size can also be adjusted depending on the goal of the model. If, for instance, the current balancing market in the Netherlands should be modelled, then the aFRR capacity should be around 300 MW. The market size is different across all European countries. The modeller must ensure that the chosen aFRR capacity is enough to meet the aFRR demand. Specifically, energy storage systems providing aFRR a larger market implies that it will take longer for the market to saturate, and thus the impact of new aFRR-providing storage systems will be lower.

4.6.4. mFRR design options

mFRR is from a modelling perspective similar to aFRR. Therefore the design choices are the same as discussed in subsection 4.6.3. Some of the changes between mFRR and aFFR is that mFRR is a slower reserve type. Therefore, design options in parameters like the control cycle, FAT response time and market size are generally significantly larger than aFRR.

5

Specific Purpose Energy Storage Modelling

In this chapter, the modelling choices and methodology will be discussed. A part of this methodology was to create single-purpose models that serve as convenient building blocks for the more complex complete energy system model, which will be discussed in chapter 6. These single-purpose models will first be examined on a conceptual level. Then the implementation of the single-purpose model will be discussed, followed by results and a discussion on what part of the models will and will not be used in the final complete energy system model.

5.1. Energy system optimisation modelling and tools

An energy system optimisation model is an energy system model that is solved using optimisation techniques. Generally, solving optimisation functions entails finding an optimal value for an objective function built up out of decision variables bound by constraints. For an energy system, this can be finding the minimal operation costs (objective function), while generators must meet demand (constraints). The dispatch of the generators (decision variables) will need to meet this demand [33].

Energy System Optimisation Models (ESOMs) are essential in making investment decisions, grid expansion planning and other political goals. This chapter explains the central concept of ESOM and different design choices that can be made, and which ESOM tools were used in this thesis [34].

5.1.1. ESOM tools categorisation and design choices

Once the optimisation problem is defined, it is required to select a tool that can solve such problems. This tool is highly dependent on the characteristics and nature of the optimisation problem. A study from 2018 [35], categorised optimisation tools based on spatiotemporal resolution, purpose, technical and economic parameters and modelling approach.

Purpose

The purposes of the optimisation tools can be categorised in four types:

1. Power System Analysis Tools (PSAT)
2. Operation Decision Support (ODS)
3. Investment Decision Support (IDS)
4. Scenario analysis (S)

Tools with a PSAT purpose look into power systems with great detail. Here the analysis can be made on, for instance, dynamic stability or fault-induced transients, etcetera. ODS-oriented tools try to optimise the operation dispatch of energy systems. IDS tools try to predict optimal investment decisions. These tools generally operate on a larger time scale. The scenario tools are for future long-term analysis within the electricity sector. They can be used for evaluating the impact of specific policies. ODS/IDS oriented optimisation will be the main purpose for this thesis.

Spatiotemporal resolution
This decision covers the resolution a simulation can run based on space and time. For systems with higher renewable penetration, a higher temporal resolution is required due to the unpredictable behaviour of renewable sources. While for investment decisions, the time interval is in the range of days. Therefore, the choice of the spatiotemporal resolution is mainly dependent on application [35]. Since this thesis tries to capture the macro balancing behaviour, the simulation step size is set to 15-minute intervals since this is how the aFRR data is received. Furthermore, to keep the modelling, manageable temporal effects are neglected. This implies that, for instance, the area control error (AGC) is equal everywhere.

Technological and Economic parameters
In this part of the categorisation, there are a lot of technical/economic options that can be distinguished. These have to do with the types of generation, energy storage technology, grid topology, demand sectors, demand elasticity, demand side management, costs, markets, and emissions [35]. The main technical constraints in this thesis will be related to storage modelling, so keeping track of the state of charge, and technical parameters such as charging/discharging efficiencies and self-discharge rate.

Approach and methodology
Energy system optimisation models generally follow three approaches: top-down, bottom-up and hybrid. Bottom-up models are used for more detailed descriptions of subsystems, like energy storage behaviour. Top-down approaches cover the overall system and look more at economics [35]. These approaches will be further investigated in section 5.1.2. The methodology is the way the problems are modelled and solved. This thesis covers optimisation models and will therefore use linear programming and mixed integer linear programming (MILP) .

5.1.2. Implemented modelling methodology and approach

It is quite rare for a single ESS system to gain a proper return on investment when it can only perform one grid service. To make investing in these ESS profitable, they should be able to perform multiple services at once. An example of a combination could be voltage support, power quality and transmission upgrade deferral. Combining ancillary services is possible since some do not change the state of charge significantly. Providing multiple services means that there can be multiple cash flows from the different services. The value the storage system provides can be measured in two ways. Namely, the actual touchable income for the service provided, but the value can also be expressed as the costs saved by implementing such a storage system [5][36].

Modelling approach
A study from 2021 [37], looks at the value of stacked services and the influence of storage systems on the markets. The modelling of all these services is done using optimisation techniques. Regarding the optimisation-based modelling of a storage system, there are two ways to examine a problem. The study distinguishes these two approaches as the lower-level problem (LLP) and the upper-level problem (ULP). These two approaches are visualised in Figure 5.1.

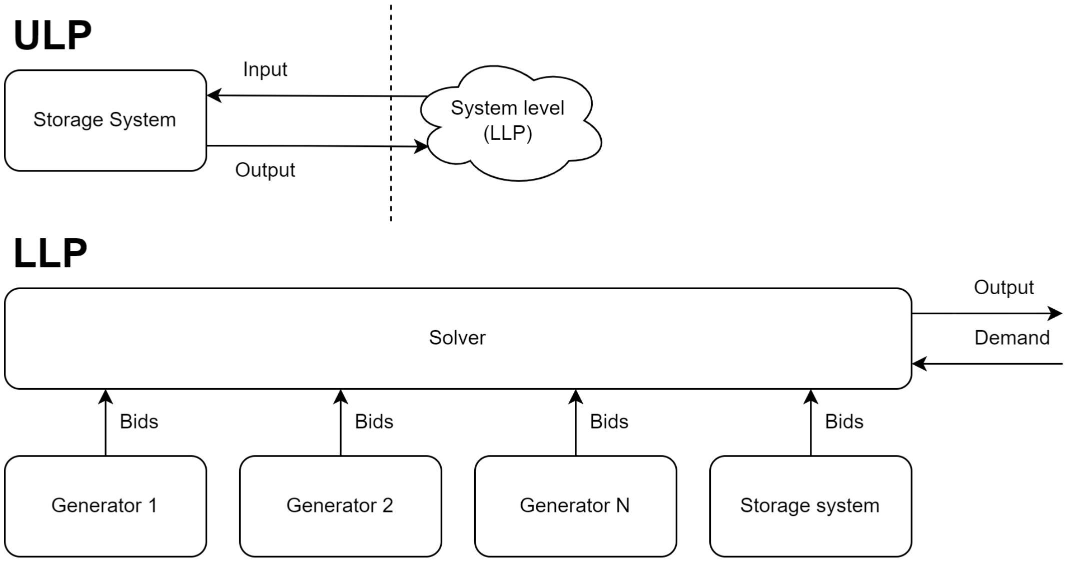

Figure 5.1: Visualisation of two modelling approaches, which are system oriented (LLP) and unit orientated (ULP)

ULP-type models describe single-unit systems with a single objective. The main objective of the storage systems described in this thesis is to maximise profits. ULP models take information from the energy system, such as demand or electricity prices, to optimise its dispatch profile. For ULP models, this dispatch does not influence the energy system. LLP type models look at the behaviour of the total energy system. This modelling methodology has a complete system-oriented objective function, which is maximising social welfare and minimising the total system costs for most energy system models. With this methodology, storage systems do influence the energy system.

So to summarise, there are multiple services from which a storage system can optimise its dispatch portfolio. This modelling can be done using two different modelling methodologies, system-oriented (LLP) and storage unit-oriented (ULP).

Modelling methodology
The models have been made in Matlab with the help of the Optimisation Toolbox extension [38]. This toolbox allows for functions such as linprog() and intlinprog(), which will solve linear optimization problems (LP) and mixed integer linear optimisation problems (MILP). This toolbox forms the basis for most of the optimisation models. A limitation of this toolbox is the limited amount decision variables for which it will still solve the problem since when the decision variables go into the thousands linprog() starts to fail. Therefore it was necessary to make these optimisation models with a limited time horizon instead of whole years. Furthermore, the modelling tool PyPsa has also been used to verify some of the LLP Matlab models are presented.

5.2. Single purpose models

In this section, research question 4 will be answered. This is done by discussing multiple single-purpose models, these single-purpose models will describe specific energy storage services from different angles. These models form the building blocks for the complete energy storage model. An example of a single-purpose model is an energy storage model that only performs arbitrage on the system level (LLP) or on the storage unit level (ULP). Later in this section, multiple single-purpose models were combined, for instance, both ULP and LLP arbitrage only, or a model that does arbitrage and aFRR on only storage unit level (ULP).

The structure of each subsection is as follows: first, a conceptual model is given, which is the sub-model described only using equations. Secondly, the Matlab implementation is briefly discussed with results and lastly, a discussion of the model.

5.2.1. ULP energy storage arbitrage model

The upper-level energy storage arbitrage model is an optimization-based model trying to maximise its profits from the day-ahead market (DAM). The time step of this model is chosen in such a way as to match the DAM bidding resolution, which is hourly. Similarly, the electricity prices obtained from Entsoe [39] are also given hourly.

In equation 5.1, the objective function is given. The objective is to maximise profits. λ_t is the electricity price for each hour, P_t^{dch} is the discharge power of the energy storage system and P_t^{ch} is the charging power of the storage system for every hour. SOC_t is the state of charge at t.

$$max \sum_{t=1}^{24} \lambda_t (P_t^{dch} - P_t^{ch}) \tag{5.1}$$

The decision variables given as:

$$P_t^{dch} \geq 0, P_t^{ch} \geq 0, SOC_t \geq 0 \qquad \forall t \tag{5.2}$$

This objective function is subject to the following constraints:

$$SOC_{t+1} = \eta^{SDrate} SOC_t + P_t^{ch} \eta^{ch} - P_t^{dch} \frac{1}{\eta^{dch}} \qquad \forall t \tag{5.3}$$

Here SOC_t indicates the current state of charge, which will change based on the charging and discharging power and their relative efficiencies.

$$P_t^{ch} \leq P^{ch,max} \qquad \forall t \tag{5.4}$$

$$P_t^{dch} \leq P^{dch,max} \qquad \forall t \tag{5.5}$$

$$SOC_t \leq SOC^{max} \qquad \forall t \tag{5.6}$$

The $P^{ch,max}$ and $P^{dch,max}$ is the maximum charge and discharge power, and SOC^{max} is the maximum allowed state of charge.

$$SOC_0 = 0.5 SOC^{max} \tag{5.7}$$

$$SOC_{24} = SOC_0 \tag{5.8}$$

SOC_0 indicates the starting state of charge. It is essential to define this. Otherwise, the starting SOC will be whatever is optimal. Also, to keep the storage system from completely discharging, the end state of charge is set to be equal to the starting state of charge.

Results

The conceptual model has been implemented in Matlab, for which the storage system behaviour is seen in Figure 5.2

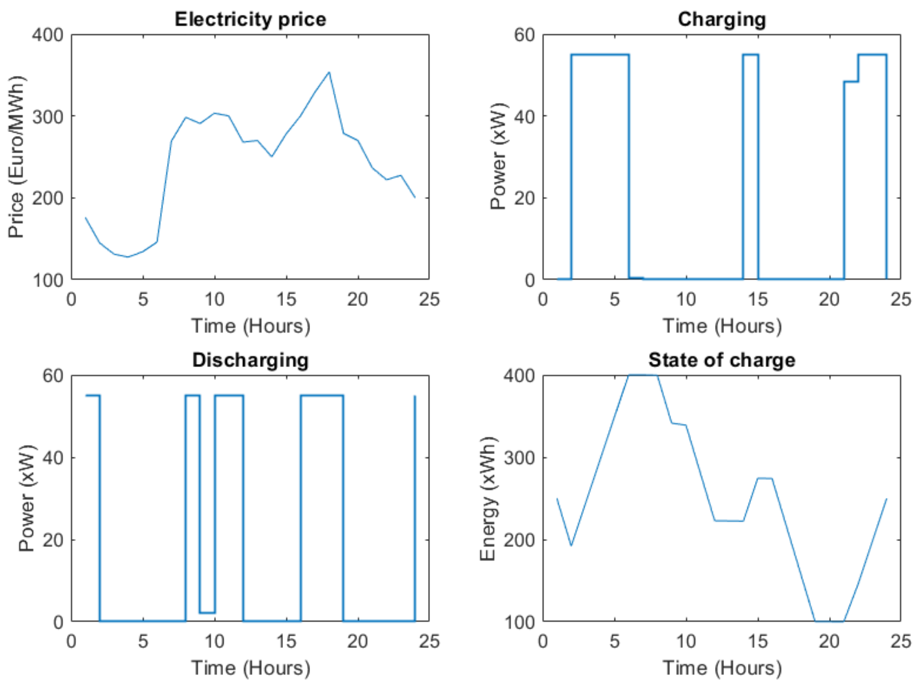

Figure 5.2: ULP arbitrage results, given the electricity price as input. And charging and discharging behaviour and state of charge as output

Considerations and discussion

Modelling smaller storage systems generally allows for the ramping rate to be neglected. However, this is not true for every storage system since pumped hydro systems have a significant ramping rate that should be considered. Another vital factor to include in the objective function are the operating costs. Especially for battery storage systems like Li-ion batteries since the system's lifetime can be significantly reduced due to the charge and discharge behaviour. Therefore for battery systems (excluding redox flow and hydrogen storage), technical considerations like cyclic ageing should be included in the optimization function.

In this model, the starting and ending state of charge are the same, and the optimization window is set for 24 hours. This time window is sub-optimal as the storage system's behaviour is limited since it does not take future days into account. For practical systems, it is advised to increase the optimization horizon, which will increase performance as it looks further into the future and can make more profitable dispatch decisions.

5.2.2. LLP energy storage arbitrage model

A paper from 2021 [37] discusses a conceptual model for an energy LLP arbitrage model. Based on this model, the following objective function of the LLP arbitrage model could be made:

$$min \sum_{t}^{T}(\sum_{i}^{N^{gen}} \lambda_{t,i}^{gen} P_{t,i}^{gen} + \sum_{j}^{N_{st}} \lambda_{t,j}^{st,dch} P_{t,j}^{st,dch} - \sum_{j}^{N^{st}} \lambda_{t,j}^{st,ch} P_{t,j}^{st,ch}) \tag{5.9}$$

The objective is to minimise the overall system costs, which are mainly dependent on the variable costs of the generators given by $\lambda_{t,i}^{gen}$ (in Euro/MWh) multiplied by the corresponding generation $P_{t,i}^{gen}$ (in MW). $\lambda_{t,i}^{gen}$ changes over time in real-life systems since it is dependent on fluctuating gas and coal prices. However, in this model implementation, these are set constant over time.

$\lambda_{j}^{st,ch/dch}$ is the price offered by the storage system for charging and discharging, which is set to zero to be always accepted by the market clearing. The power output of the storage system is given by $P_{t,j}^{st,dch}$ and $P_{t,j}^{st,ch}$. When $P_{t,j}^{st,ch}$ is positive, it means that the system is charging and thus increasing load and when $P_{t,j}^{st,dch}$ is positive, the storage system is discharging and therefore "decreasing load" or

helping meet demand.
A decision variable not given in the objective function but included in the model is SOC_t, which keeps track of the state of charge. Further is given that all the decision variables are greater or equal to zero.

The objective function is subject to the following constraints:

$$P_t^{demand} = \sum_{i}^{N^{gen}} P_{t,i}^{gen} + \sum_{j}^{N^{st}} P_{t,j}^{st,dch} - \sum_{j}^{N^{st}} P_{t,j}^{st,ch} \qquad \forall t \tag{5.10}$$

$$P_{t,i}^{gen} \leq P_{t,i}^{gen,max} \qquad \forall t, i \tag{5.11}$$

$$P_{t,i}^{ess,ch} \leq P_{t,i}^{ess,max} \qquad \forall t, i \tag{5.12}$$

$$P_{t,i}^{st,dch} \leq P_{t,i}^{st,max} \qquad \forall t, i \tag{5.13}$$

$$SOC_{t+1} = \eta^{SDrate} * SOC_t + P_t^{ch}\eta_{ch} - P_t^{dch}\frac{1}{\eta_t^{dch}} \qquad \forall t \tag{5.14}$$

$$SOC_t \leq SOC^{max} \qquad \forall t \tag{5.15}$$

The descriptions of the constraints are given below:

- 5.10 is responsible for matching generation and demand. Hereby the demand is given by P_t^{demand} and can be met by the generation of the storage systems and generators.
- 5.11 ensures that the generators are bound by their maximum power output capacity given by $P_{t,i}^{gen,max}$.
- 5.12 and 5.13 make sure the discharge and charge rate is bound by the rated storage power $P_{t,i}^{st,max}$.
- 5.14 describes the state of charge for each storage system, which changes every time interval. This is based on the self-discharge, energy charged, energy discharged and the corresponding charging and discharging efficiencies.
- 5.15 limits the total energy stored in the storage system.

Results and discussion
This model was implemented using Matlab and compared to a PyPsa implementation of the same system. This comparison is given in Figure 5.3.

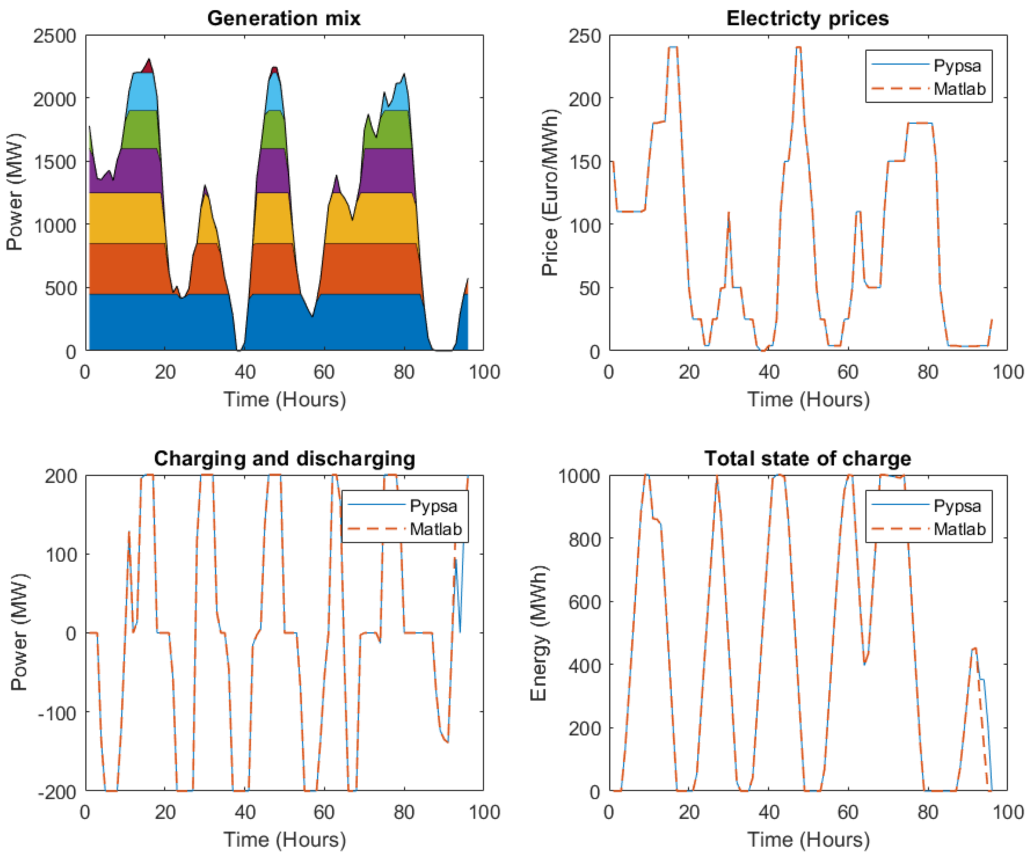

Figure 5.3: LLP Matlab model comparison with PyPsa model, the top-left plot shows generation mix by PyPsa with the generators indicated by the coloured areas, the top-right plot shows electricity prices, and the bottom two plots show the storage behaviour

The results of the Matlab model and the PyPsa model are almost the same, indicating that PyPsa uses a similar method of solving these systems as described by the Matlab model. There is some error in the Matlab model however, as it can be seen that for the last few time steps, the models do not match anymore. This error is explained by the fact that constraint 5.14 is undefined for the last time step in the Matlab model. Since the final model will run on a moving optimization horizon, this difference can be neglected.

5.2.3. Combined ULP and LLP arbitrage model

This model combines the earlier discussed models, namely the LLP arbitrage model and the ULP arbitrage model. A simplified description of this model is seen in Figure 5.4. The ULP storage system blocks are the same as described earlier, with the storage parameters, price profile, energy storage capacity and power capacity as primary inputs. The output of the ULP storage block is a storage bid, which has been set to 0 Euro/MWh. Moreover, the bid size (in MW) is set equal to the output of the ULP optimisation, so it is equal to the storage system's charging and discharging profile. This storage bid will be added to the cumulative storage bids block. In the cumulative storage bid blocks, all the storage bids are added together and treated as one single storage system with a fixed charging and discharging profile.

In the first loop, the electricity price is calculated (LLP), and then this price is sent to the first storage system (ULP). This storage system will then calculate its optimal charge and discharge profile, and this addition will be added to the total system level (LLP), which may influence the electricity price. This model will do this for all the storage systems. It can occur that one storage system charges, and another storage system will discharge in the same time interval. If this happens, the charging and discharging will be netted.

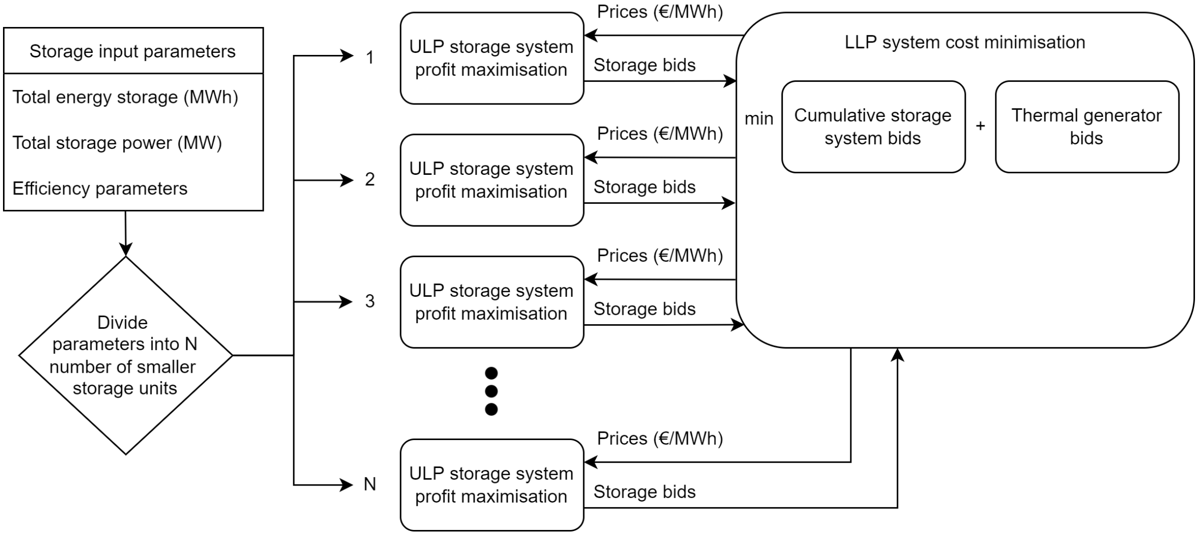

Figure 5.4: The visualisation of the ULP and LLP combined arbitrage model

Implementation
This model was simulated in an eight-generator system with varying capacities and variable costs. The system parameters can be found in Table 5.1. The storage system implemented has a capacity of 200 MW and can fully output that power for 5 hours. The self-discharge rate is 0.9975 every hour, and the charge and discharge efficiency is 95%.

Generators/Storage Systems:	G1	G2	G3	G4	G5	G6	G7	G8	SS
Capacity (MW):	10000	450	400	400	350	300	300	2500	200
Variable Costs (Euro/MWh):	0	4	25	50	110	150	180	240	0

Table 5.1: Thermal generator capacity and variable cost overview

The model optimises the storage system dispatch over four days. The demand curves from the ENTSO-E transparency platform represent the demand for four days in the Netherlands.

Results
The results of this simulation can be seen in Figure 5.5.

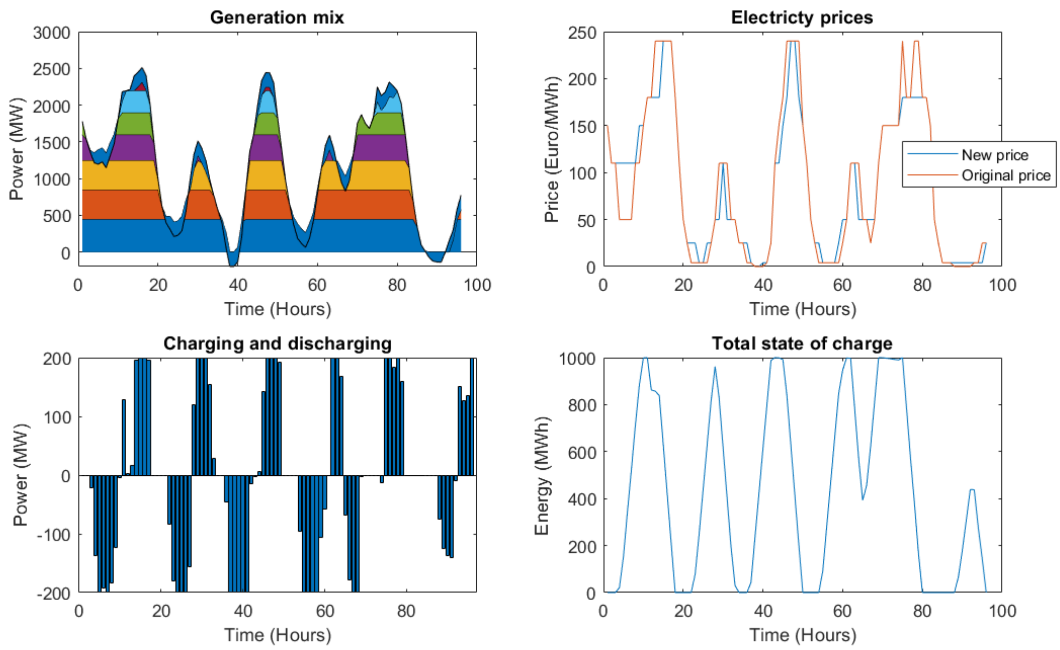

Figure 5.5: Results of the ULP and LLP combined arbitrage model. The colours in the top-left plot indicate the different generators, and in dark blue filling the peaks and valleys, the influence of the storage system is shown

Here the generation mix is seen in the top-left plot, in order to make this plot more readable, the largest base generator has been excluded. The changes in electricity price due to added storage is seen in the top-right plot. Furthermore, the bottom two plots show the charging and discharging behaviour of the storage system(s) and the total state of charge.

Discussion

The generation mix plot from Figure 5.5 shows the active generators to meet demand stacked from cheapest (bottom) to most expensive generators (top). The storage system influence can be seen as the filling of the peaks and bottoms. The electricity price plot shows that the price generally becomes less volatile as extremely high and low prices become less frequent. It can be said that the influence of storage systems will lead to a more stable energy system, this is because the prices and load curves become less volatile.

Comparing Matlab results with PyPsa

The model described in the previous section has been remade with the same input parameters using PyPsa to compare it with the Matlab model. This comparison aims to see where the models diverge from each other. PyPsa is a system-level optimisation model (LLP). So therefore, the main objective is to minimise total system costs, whereas the Matlab model both minimises the system costs and maximises the revenue of the storage system(s). The comparison plots are seen in Figure 5.6.

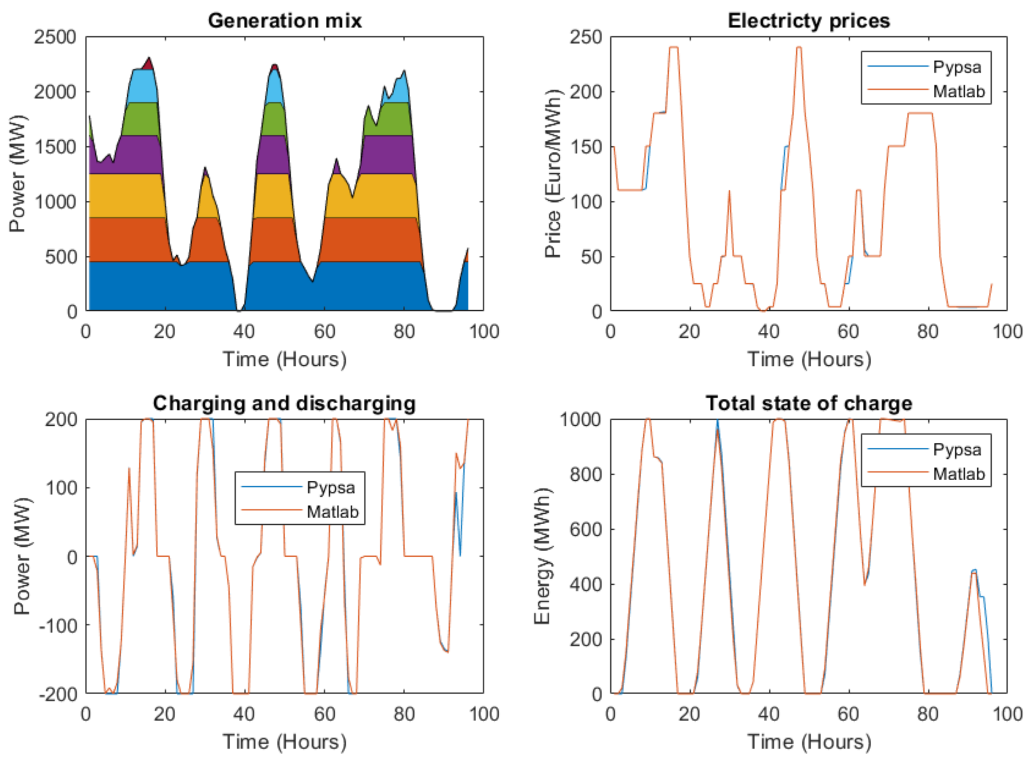

Figure 5.6: Comparing the (ULP/LLP) Matlab model with the (LLP) PyPsa model, based on generation mix of PyPsa (The colours represent the different generation sources), electricity prices, charging and discharging behaviour and state of charge

From the figure, it can be seen that the resultant behaviour of both these models is almost identical. These results show that the value the ULP model gains by maximising profit is congruent to the system costs saved by utilising energy storage systems. This also answers research question 3, since these results show that profit maximisation ULP systems produce similar results as modelling storage using a system minimising approach.

Some differences between PyPsa and Matlab are found, namely that it can be seen that the prices of both plots are not always the same. Both models use Lagrange multipliers to generate the electricity prices (shadow price of the equality constraints). The difference in prices could be because PyPsa uses a more detailed model to determine the prices. What both storage systems in both models try to do is to maximise the value gained from the storage system (maximise the value by minimising system costs or by maximising profits), so what will happen is that the storage units will adjust generation/demand in such a way that they move close to a price jump. So to illustrate: if demand rises by 0.01 MW, it is possible to jump from 110 Euro/MWh to 150 Euro/MWh in the Matlab model, while in PyPsa, this does not happen, this is because the Matlab model is less precise, but this is not a significant problem since in real energy systems, there are a lot more generator bids making these jumps less significant.

Another noticeable difference between the two models is at the end of the simulation horizon. This difference is mainly due to the state of charge being unbounded in the last step of the Matlab model. Since this model is meant to be used as a moving horizon model, this error has been ignored since data further in the future is less exact and will be updated as the horizon moves forward.

Lastly, differences in discharging, charging, and prices are also due to the limited precision of the Matlab model. This is because the Matlab model divides a storage system into N-smaller sections, which can cause extra errors. These errors can be made smaller by slicing the storage model into even smaller sub-storage systems, making the model more precise.

This part mainly discussed a less accurate and more complex Matlab model having similar results as the simpler PyPsa model, indicating that the Matlab model might be redundant. However, there are some advantages of this model. Firstly, it allows for more storage system-oriented programming, and it becomes easier to introduce physical phenomena like cyclic ageing and thermal limits. It is also possible to introduce forecast errors and different forecasts for different storage systems and simulate a system with many different storage systems by changing efficiency parameters.

Modelling storage systems in this way will also make it more straightforward to introduce balancing markets, for which the storage system can optimise its dispatch portfolio. On the other hand, if someone looks to only capture the most dominant effects of Arbitrage, then the results validate that using an LLP-based modelling tool is perfectly fine

5.2.4. Peak shaving models

Many storage system applications discussed in 3.1 can be described as peak shaving at a certain topological level in the electricity power network. There are multiple methods to shave peaks, the simplest one is to set a constant shave level, and another is to shave the maximum level to the maximum capacity the storage system is able to do. A large part of storage systems will be doing peak shaving. This service will be conducted in a distributed manner in the electricity network, and is mainly dependent on local conditions like the thermal capacity of certain lines or individual loads. Therefore it is challenging to translate this into a complete system-level problem. To partly overcome this, the assumption will be made that all peak shaving activities will happen when the grid is most likely to be congested, which is at times when daily demand peaks.

Constant Shave Level

An adaptation of the arbitrage model is sufficient for systems where a single shave level is required, such as on distributed lines or microgrids. Using the arbitrage model allows the system to operate cost-effectively since the battery generally charges at times when the price is low. This adaptation only requires the addition of an inequality constrain, which sets the maximum load to a certain level. This can be seen in equation 5.16.

$$P_t^L - P_t^d ch - P^{Shave} \leq 0 \tag{5.16}$$

Where P_t^L is the measured load and P^{Shave} is the shave level which the user sets. A downside of this model is that it is still based on an arbitrage model that optimises profit. Since this model is arbitrage based, there can be dips at time instances which used to be peaks. This is to still maximise profit.

Load levelling model

A storage system providing load levelling will attempt to keep the load as flat as possible. This model is built upon the arbitrage model with two shave levels, one upper and one lower shave level. The model brings the two shave levels closer together every loop until the model stops converging. Similarly, as in the model with the constant shave level, the arbitrage component causes dips. This dip can be seen in Figure 5.7 on the place where the demand previously had a peak.

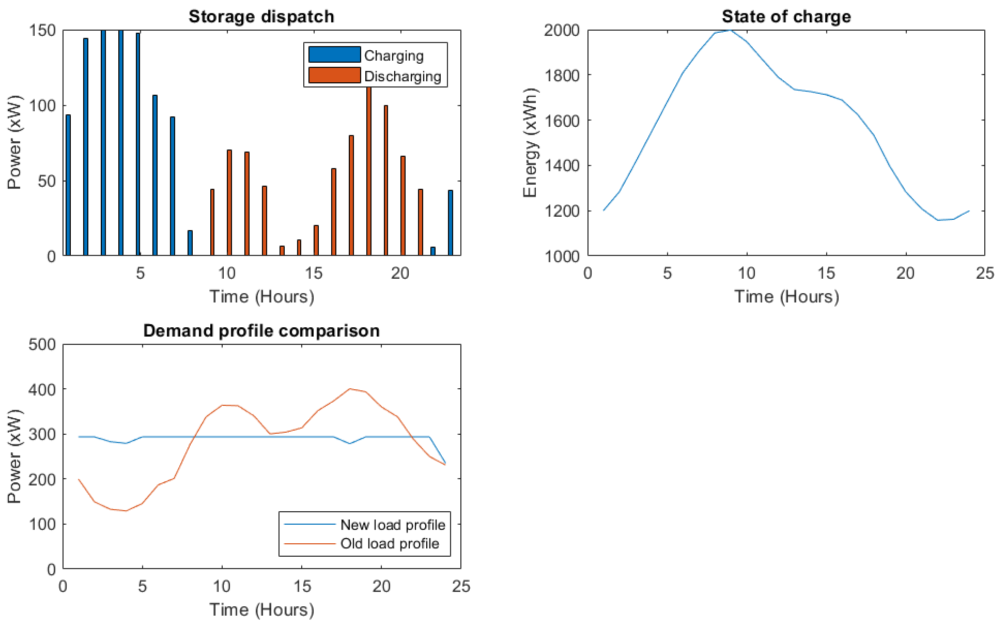

Figure 5.7: Iterative load levelling model results, comprising charging and discharging behaviour, state of charge and demand profile changes

Besides the dipping behaviour, this model implementation is also slow, especially if it has to be scaled to larger time horizons. This is mainly due to the model requiring to solve an optimisation problem every time it loops, and the limits move closer together.

Minimum shave level

This optimisation problem minimises the peaks and, therefore, only has to minimise one decision variable, namely the shave level: L^{shave}. The model is based on mixed integer linear programming, and the objective function of this model is given by 5.17.

$$min L^{shave} \tag{5.17}$$

The decision variables are given by:

$$P_t^{ch}, P_t^{dch}, SOC_t, P^{load}, u_t, d_t, L^{shave} \geq 0 \qquad with \quad u_t, d_t \in \{0,1\} \qquad \forall t \tag{5.18}$$

Besides the regular storage constraints, the optimisation model is now also constrained by 5.19.

$$P_t^{load} - P_t^{dch} + P_t^{ch} - L^{shave} \leq 0 \qquad \forall t \tag{5.19}$$

Since the model tries to minimise the peaks, it can sometimes happen that the storage system charges and discharges simultaneously to remove stored energy. Therefore it was necessary to adjust and add some constraints to mitigate this behaviour. These new constraints are given below:

$$P_t^{dch} - d_t P^{max} \leq 0 \qquad \forall t \tag{5.20}$$

$$P_t^{ch} - u_t P^{max} \leq 0 \qquad \forall t \tag{5.21}$$

$$u_t + d_t \leq 1 \qquad \forall t \tag{5.22}$$

In these equations, u_t and d_t are binary decision variables that can only be 1 or 0. These are coupled with the maximum discharge and charge rate and ensure it is no longer possible to charge and discharge in the same time interval.

Results and discussion

This model has been implemented and simulated. The results can be seen in Figure 5.8.

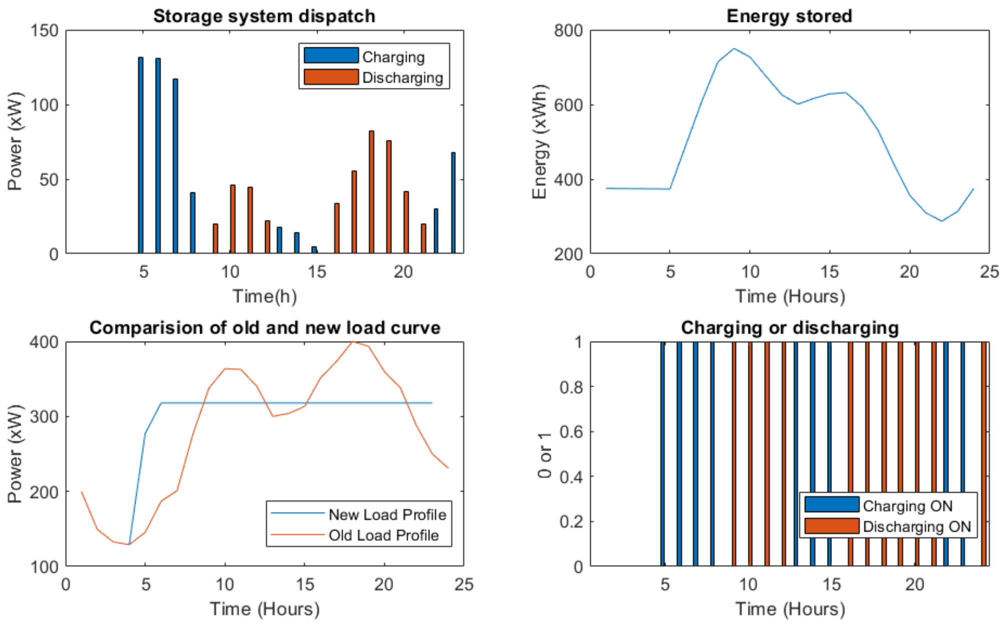

Figure 5.8: Results of the peak shaving algorithm, with the charging and discharging behaviour, state of charge and load curve comparison

In the bottom right plot of the figure, the active binary decision variables are visualised. Therefore this plot shows if the storage system is allowed to charge or discharge. For the state of charge or energy stored, it has been chosen that the storage system starts and ends with 50% SOC to make the model function for moving horizon simulations.

A downside of this peak-shaving model is the behaviour during the charging, as seen from the load curve figure. The new load curve has a very high ramping rate due to the charging of the storage system. Ideally, the implemented peak-shaving algorithm in the complete system model should also have the means to reduce this fast ramping behaviour by, for instance, implementing a way to also shave the valleys.

5.2.5. aFRR analysis based models

This part of the thesis investigated the aFRR behaviour. The main objective of this analysis was to find relations between load, day-ahead market prices and energy prices of the aFRR market and gain better insight into overall aFRR behaviour. This is to create a simpler model to simulate the aFRR behaviour and then make a storage model that can optimise based on this simplified aFRR model. This section will cover multiple approaches taken when it comes to aFRR modelling. This section will examine why some of these fell short and why other model implementations were more promising than others.

Data sorting and probability models

The first idea to model aFRR was to create a stochastic optimisation-based model since these optimisation models are not deterministic and can capture the randomness of the aFRR control signal. With stochastic optimisation, the objective is to optimise over a set of probabilities that a specific regulation request had to be met by using a tree-like structure, with each branch representing an aFRR demand scenario. To create this model, it was necessary to find the probabilities that a specific aFRR request can be made. This has been done in Figure 5.9

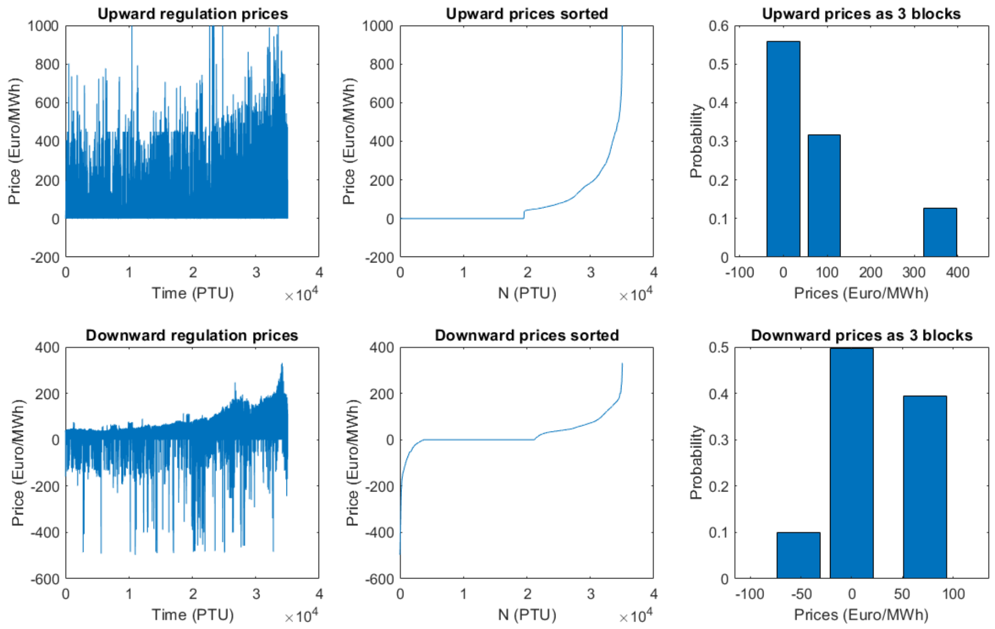

Figure 5.9: Yearly aFRR energy price, aFRR energy price sorted and adjusted to 3 blocks for both upwards and downwards regulation. (2021-Netherlands [39])

To further elaborate on the two plots on the most right, these are the aFRR prices sorted on probability. This plot was made by first creating price intervals and calculating the probability that the price was in this interval. Next, the average of this interval was calculated. The interval's probability and average price are then plotted in this figure.

The next step was to start on the stochastic optimisation-based model. However, this proved challenging as just one PTU generates six different regulation scenarios, with that six different states of charge and storage dispatch profiles. One day of simulating meant 6^{96} different scenarios, assuming no further optimisations are made to reduce this number. Since this required an immense amount of decision variables and computing power or having to implement significant simplifications, this idea was not further investigated. A good outcome of this investigation is that the figures created provided valuable insights into regulation behaviour.

Regression based modelling

Another approach was to approximate the aFRR energy prices as a function of the demand. Here the idea was to be later able to move these curves upwards or downwards based on the number and capacity of newly introduced storage units participating in the aFRR market.

This model starts by approximating the day-ahead and aFRR market bidding ladders. This approximation was made using the statistics and machine learning toolbox found in the Matlab apps, which fits a nonlinear regression model on the data. This script allows users to select a time frame with the year 2021, over which the regression should be made. The function used for fitting was a second-degree polynomial, and the results can be seen in Figure 5.10.

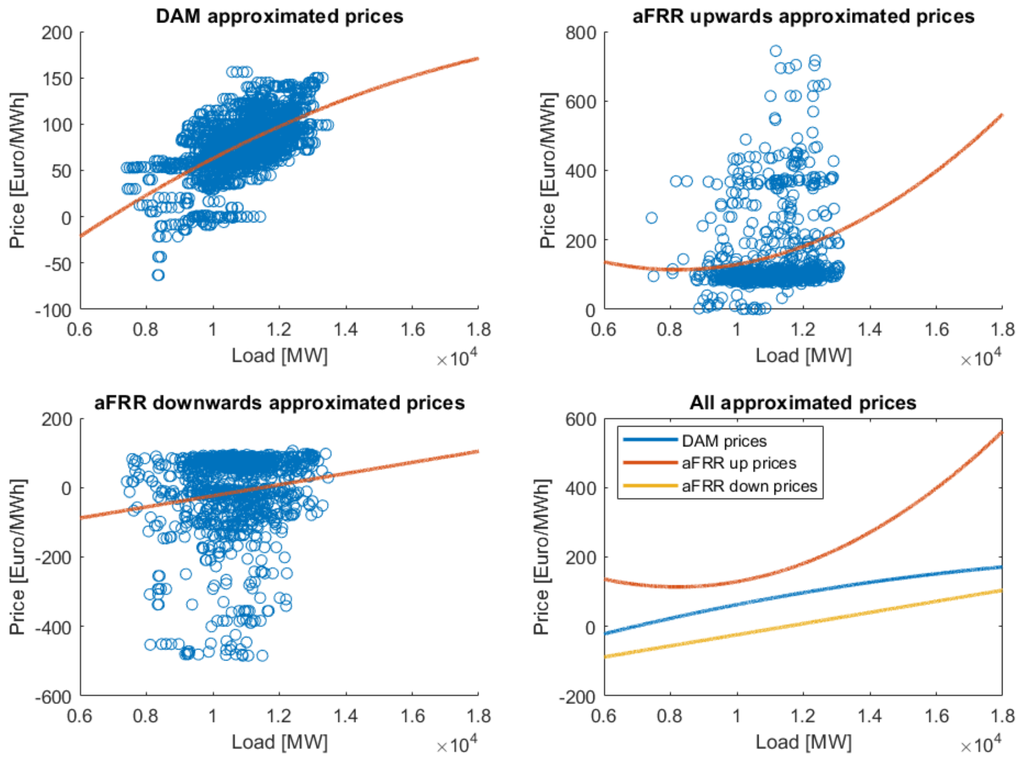

Figure 5.10: aFRR data and fitted curves

In the figure, four plots are shown, and three show scatter plots of the energy prices over the corresponding demand. This figure shows that as demand increases, so do the energy prices of the DAM and aFRR markets. Through these scatter plots, the nonlinear regression model is plotted. In the bottom left plot, these models are plotted in one figure. For this time frame (and other time frames), the energy price of upwards regulation is more than the DAM prices, and the DAM prices are more than the downwards regulation energy prices. It is important to note that this regression model is only valid for loads between 7 GW and 14 GW, as there is no data outside this window.

The results of this approach can differ quite a lot since this regressed model is only accurate for the specific time window chosen. A larger window leads to overall worse performance. Ideally, the yearly data can be divided into multiple smaller sections to which a specific regression model is assigned. A downside of this model is that it is poor at capturing extremely high and low prices, as when the regressed model is compared to actual aFRR prices, it can be seen that the model has much less extreme values. To visualise this Figure 5.11 is given. Here can be seen that the regression model averages between the extremely high values and the more common lower price values.

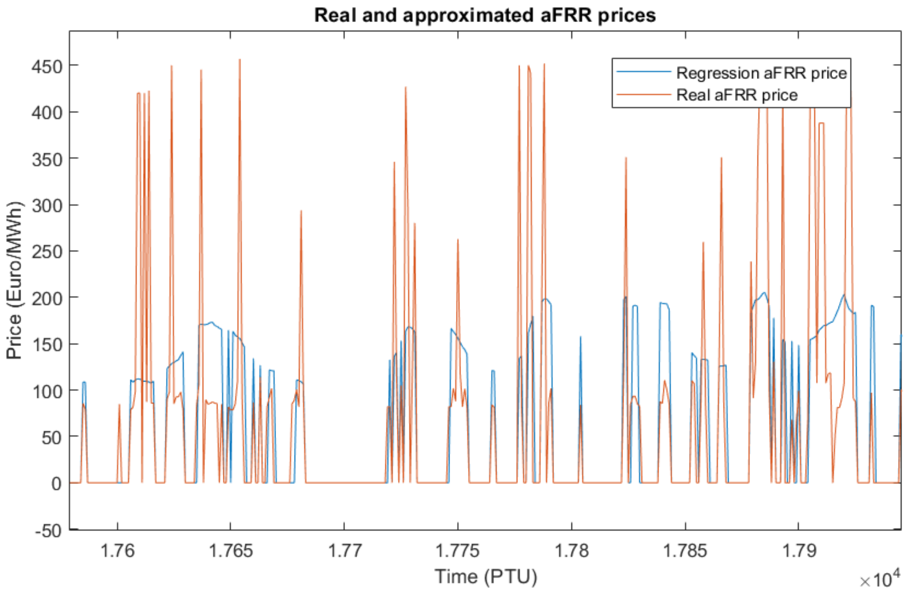

Figure 5.11: Real aFRR prices compared to the regression model based aFRR prices

As seen in the figure, the regression model is an averaged version of the actual aFRR price and therefore shows that there is more going on when it comes to determining the aFRR energy prices. This insight contributed to the aFRR energy pricing model used in the final design, which is based on the DAM and aFRR energy demands.

Reactive aFRR model

This model purely looks at the behaviour of a storage system when it is fully committed to providing aFRR, so no optimisation takes place here. This model aims to see the impact of participating in the aFRR market on the overall demand. The storage impact on the demand mainly depends on the need to charge/discharge based on the aFRR volumes.

This model operates as a ULP storage model operating in a merit order-based system, which means that the storage system will have to fully activate based on the committed capacity. So this is not a pro-rata system where all the balance service providers have to activate the same percentage of power [31].

To ensure that the storage system does not fully discharge within the committed hours, it can only bid capacity based on the current state of charge such that it is impossible to discharge fully. To illustrate, if a storage system has a SOC of 0.7 and stores a total of 24kWh of energy, then the storage system can only commit (1-0.7)*24kWh/24 hours = 0.3kW of downwards regulation. The formulas for both upwards and downwards capacity is given in 5.23 and 5.24

$$P^{C,up} = \frac{C^{up} P_{max} SOC}{T^{sub}} \tag{5.23}$$

$$P^{C,down} = \frac{C^{down} P_{max} (SOC - 1)}{T^{sub}} \tag{5.24}$$

Here the P^{up} and P^{down} is the capacity committed, $C^{up/down}$ is an adjustable parameter to for instance increase/decrease storage aFRR participation. SOC is the state of charge, and T^{sub} is the interval duration for which storage systems are allowed to bid. This model assumes that the capacity bid is constant over the entire period. This model has been implemented in Matlab, but it became clear that due to the large capacity commitment time (24 hours), the system can only use a small part of the storage system. Therefore this method alone is not an economically efficient system in the Netherlands. For other countries, it is more viable, for instance, in Germany, where the capacity commitment can be done every 4 hours. So for the storage system to earn more income, it should be able to take more risks.

Therefore the model has been modified to commit more power and if necessary, recharge/discharge from the wholesale market. This model is visualised in Figure 5.12.

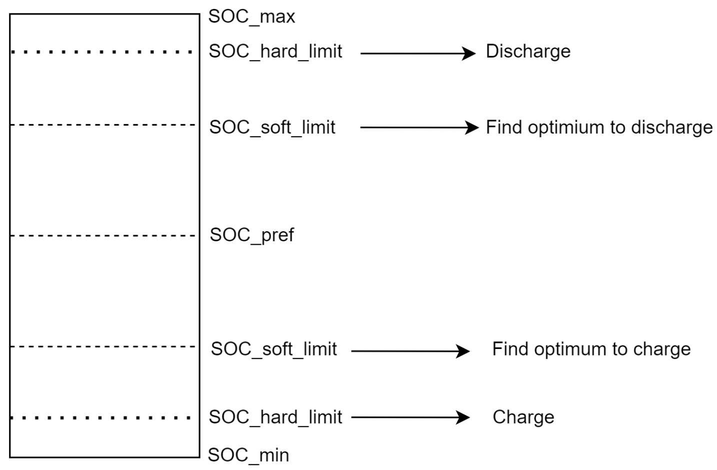

Figure 5.12: Reactive aFRR model

In this figure, a representation of the state of charge can be seen. For the storage system to take more risks and thus earn more revenue from the aFRR market, it is possible to increase the $C^{up/down}$ factor. The downside of this is that there is now a chance that the storage system can become fully discharged or completely charged. To prevent this, soft bounds have been added to the model, which starts to look for optimal periods to charge/discharge based on the most economically optimal prices within a limited time interval. If the state of charge changes such that it hits a hard boundary in that period, then the storage system will force charge/discharge.

This model has been simulated over an entire year, assuming all the capacity bids are accepted. Also, once regulation is requested, the storage system will always be first in the order of merit. Since this model is a ULP model, the influence of the storage system on the markets is neglected. Furthermore, the DAM charging is not perfectly implemented since it will charge on a minimum/maximum dam price within a 4-hour horizon. This should be improved and implemented in future versions using a peak shaving/arbitrage optimisation method.

Results and discussion

A zoomed-in version of the storage system operating can be seen in Figure 5.13. This system's energy over power ratio is set to 15, so it needs 15 hours to fully discharge when a fully charged storage system is discharging at the committed power rating.

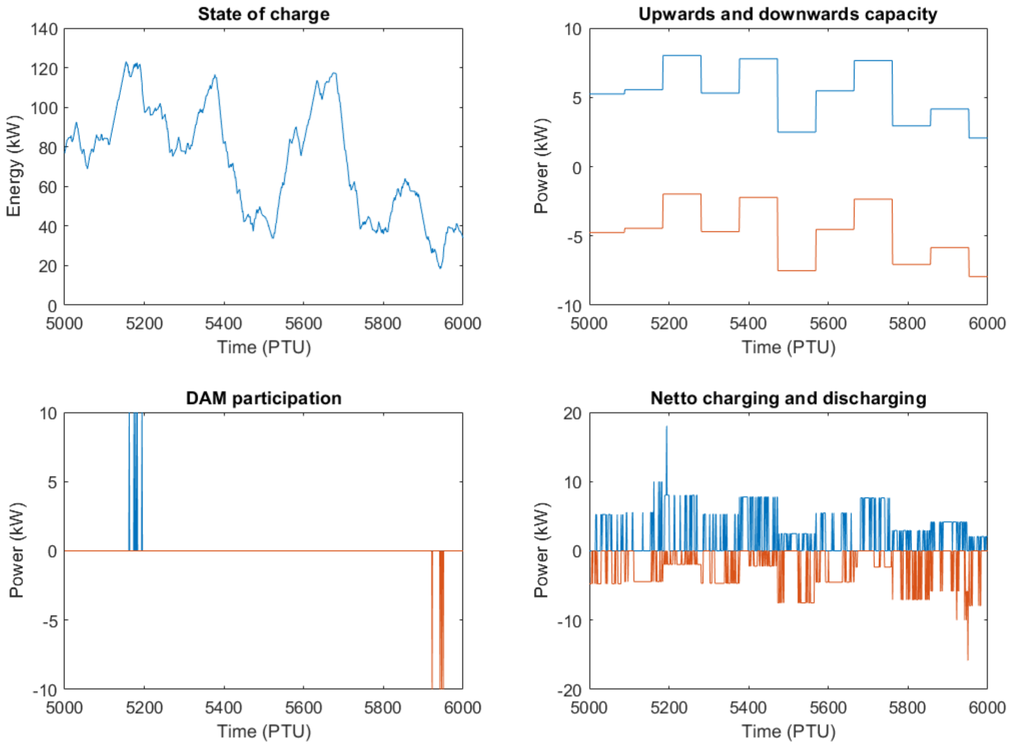

Figure 5.13: Reactive aFRR model results

In the top right plot of the figure, the capacity bids can be seen over time. As the state of charge of the storage system (top left) decreases, the downwards capacity increases, and when the state of charge increases, the upwards regulation capacity increases. In the figure, bottom right can be seen how the storage system outputs power when providing aFRR.

The behaviour of the storage system can be seen in the bottom right plot. With spikes indicating intra-day participation, currently, the intraday+aFRR output is not constrained. In future models, this should be the case, as it is advised that an optimal capacity is reserved for charging/discharging on the intra-day market.

Simplest aFRR model

This model is the simplest ULP aFRR storage model, as it is a single equation describing the system's revenue. Also, it requires easy-to-access input parameters. The model is described by equation 5.25. This will calculate the expected revenue from energy activation, assuming the storage system is always activated.

$$Rev = \frac{1}{8}\eta^{rte}P^{rated}T * (C^{up}E[\lambda^{up}] - C^{down}E[\lambda^{down}]) \tag{5.25}$$

Here Rev is the approximated revenue from aFRR mileage, η^{rte} is the round trip efficiency and is calculated by multiplying the charge and discharge efficiency. P^{rated} is the rated power of the storage system or the power allocated to regulation. $E[\lambda^{up/down}]$ is the expected energy price of the upwards and downwards regulation mileage. Moreover, lastly C^{up} and C^{down} is the expected ratio for which upwards/downwards regulation is activated, for example, the year 2021 shows that the highest possible ratios are 0.4267 for upwards regulation and 0.4709 for downwards regulation. These ratios can be roughly translated to the probability of being accepted. Here the 1/8 factor comes from the time step of 15 minutes, and due to the algorithm used in 5.2.5, which makes the system operates at half P^{rated}. So a few critical remarks, for this simplest model to work, it is required that the energy capacity is sufficiently large that the system does not have to discharge/charge a lot on the wholesale market and that the self-discharge rate is not too large. Also, this model works for a specific aFRR storage control algorithm. If other algorithms are used, it is suggested that this model is modified accordingly.

This model has been compared to the more accurate aFRR revenues, which used actual price data. Both are based on the same storage control algorithm. This model's error can be quite large (can be larger than 80%), and generally becomes larger if a smaller horizon is selected. For larger windows, the error ranges around 20%. aFRR is challenging to forecast without a large error margin, and if a modeller does not want to be bothered with a complex aFRR model, this simpler model could serve as a quick solution.

5.2.6. Optimisation based aFRR models

This section will discuss the aFRR models based on optimisation models. The first model (aFRR ULP) discusses an optimisation model with deterministic behaviour. And the second model, called the semi-deterministic ULP model, is less deterministic and will show improvements on the older aFRR ULP model. The section ends with a comparison of the two models.

aFRR (deterministic) ULP model

For the implementation of the aFRR model a time frame of 15 minutes is chosen. According to [37], a time frame of 4 seconds is necessary to simulate the regulation of the battery properly. Also, the AGC signal (which the battery has to follow) uses time set points of 5 seconds. However, since the purpose of this model is to be used on a large time frame, and regulation data is only available in 15-minute windows, this 5-second resolution has not been applied.

This model will optimise the allocated regulation capacity in such a way as to ensure that the system makes the most revenue. The objective function of this model is given by equation 5.26.

$$max \sum_{k}^{96} \frac{1}{4}\lambda_k^{E,\uparrow} P_k^{E,\uparrow} - \frac{1}{4}\lambda_k^{E,\downarrow} P_k^{E,\downarrow} + w_\uparrow \lambda_k^{C,\uparrow} P_k^{C,\uparrow} + w_\downarrow \lambda_k^{C,\downarrow} P_k^{C,\downarrow} + \frac{1}{4}\lambda_k^{dam}(P_k^{dch} - P_k^{ch}) \tag{5.26}$$

Since aFRR works with a bidding ladder, there is a need for two separate price variables. One $\lambda_k^{E,\downarrow}$ for downward regulation, where the BSP pays the TSO and a variable ($\lambda_k^{E,\uparrow}$) for upwards regulation, where the TSO pays the BSP. For downward regulation, the battery will charge such that it is loading the network; for upward regulation, it will provide energy to the network. What also can be seen from the objective function is that it uses 96-time steps which is equal to the daily amount of program time units (PTU's). A PTU is the same as the Imbalance Settlement Period (ISP). Prices of regulation are given in €/MWh and therefore it is necessary to multiply $\lambda_k^{E,\uparrow/\downarrow} P_{E,\uparrow/\downarrow}$ by $\frac{1}{4}$.

The decision variables to be optimised can be seen below in equation 5.27.

$$P_k^{E,\uparrow}, P_k^{E,\downarrow}, SOC_k, P_k^{C,\uparrow}, P_k^{C,\downarrow} \geq 0 \tag{5.27}$$

Where SOC_k is the state of charge for every 15 minutes. And $P_k^{C,\uparrow/\downarrow}$ is the subscribed capacity for both upward and downward regulation. The following constraints bound the variables:

$$P_k^{C,\uparrow}, P_k^{C,\downarrow} \leq P^{max} \qquad \forall k \tag{5.28}$$

$$P_k^{E,\downarrow} \leq P_k^{C,\downarrow} \qquad \forall k \tag{5.29}$$

$$P_k^{E,\uparrow} \leq P_k^{C,\uparrow} \qquad \forall k \tag{5.30}$$

$$SOC_{k+1} = \eta_{SDrate} SOC_k - \frac{1}{4}\frac{1}{\eta} P_k^{dch} + \frac{1}{4}\eta P_k^{ch} \qquad \forall k \tag{5.31}$$

$$P_k^{dch} = s_k P_k^{C,\uparrow} \qquad if \quad s_k > 0 \qquad \forall k \tag{5.32}$$

$$P_k^{ch} = s_k P_k^{C,\downarrow} \qquad if \quad s_k < 0 \qquad \forall k \tag{5.33}$$

$$P_k^{E,\downarrow}, P_k^{E,\uparrow} = 0 \qquad if \quad s_k = 0 \qquad \forall k \tag{5.34}$$

The AGC/control signal is modeled by s_k which is a variable that can only take values between 0 and 1.

Implementation
This model has been implemented using MATLAB. The input data is retrieved from ENTSO-E Transparency Platform. The aFRR price data (in Euro/MWh) are given in 15-minute time intervals or PTUs, for which an upward and downward regulating price is given. Similarly, the regulation volumes are given every PTU for both upward and downward regulation. Also, information on the total system regulation capacity is given. This information makes it possible to roughly estimate the AGC signal by dividing the regulation volumes by the total system capacity for each PTU. Furthermore, the regulation capacity price data (in Euro/MW) is only given once daily. Therefore it is assumed that this price remains constant over the entire day. However, in the model, the storage device has the ability to change the capacity bid every 15 minutes. However, this bid (with the 15-minute interval) can only be made once a day.

Results
The results of this model are seen in Figure 5.14.

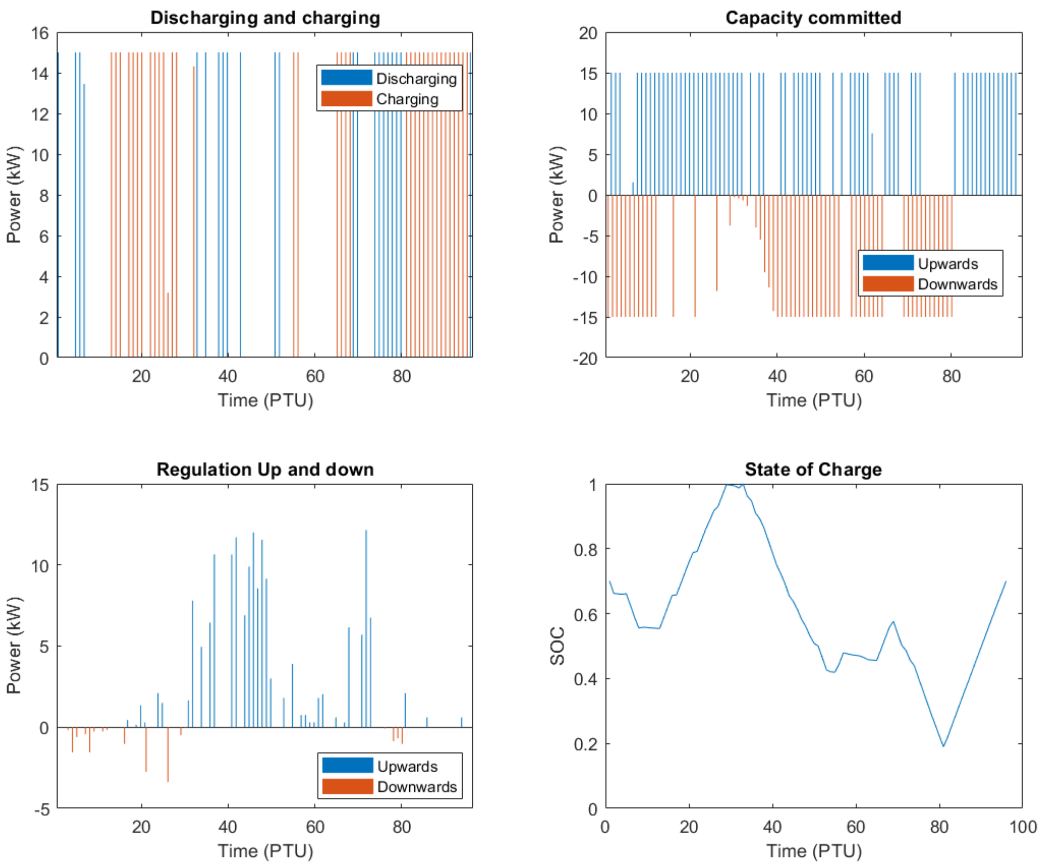

Figure 5.14: Deterministic aFRR model storage behaviour

In the figure, the storage system behaviour is seen. The plot in the top left is the storage behaviour on the wholesale market, the top right shows the capacity committed, the bottom left shows the regulation mileage, and the bottom right is the state of charge. The income for this specific day is from the wholesale market -1.32 euros. From the energy mileage, the income is 24.26 euros, and from the regulation capacity allocation, the income is 14.51 euros. These income streams result in total revenue of 38.77 euro for this day.

Discussion
From the figure can be seen that this system is entirely deterministic. The easiest way to find this is to look at the charging before the regulation energy demand is known. So this is also the major downside of this model since predicting the aFRR regulation volumes for the next day is, in practical applications,

nearly impossible. The deterministic behaviour of the model results in unrealistically high profits from the overall markets. So, therefore, there is a need to reduce this deterministic behaviour and make this model more realistic.

Semi-deterministic ULP model
The semi-deterministic ULP model does not influence the market prices, similar to the deterministic ULP model. It will also optimise the storage system's dispatch optimally over the aFRR and wholesale market. The profit-maximising objective function of this model is given by equation 5.35, which is based on [40].

$$max \sum_{k}^{96} \lambda_k^{dam}(P_k^{dch} - P_k^{ch}) + w_{\uparrow}\lambda_k^{C,\uparrow}P_k^{C,\uparrow} + w_{\downarrow}\lambda_k^{C,\downarrow}P_k^{C,\downarrow} + \lambda_k^{E,\uparrow}P_k^{E,\uparrow} - \lambda_k^{E,\downarrow}P_k^{E,\downarrow} \tag{5.35}$$

In this objective function the λ indicates the relevant price of the market, $P^{dch/ch}$ the charging and discharging in the day ahead market, $P_k^{C,\uparrow/\downarrow}$ the capacity reserved for regulation and $\lambda_k^{E,\uparrow/\downarrow}$ are the prices for the regulated energy, and $P_k^{E,\uparrow/\downarrow}$ is the average battery regulation power output during one PTU. The constraints of the system are the same as in 5.2.6.

This conceptual model has been implemented using a two-stage process in order to make this model less deterministic and thus semi-deterministic. Implementing this model without these stages will result in deterministic and unrealistic storage behaviour. For example, the storage system can predict large volumes of upward/downward regulation and charge/discharge itself before knowing that this regulation demand will happen. To reduce this deterministic effect, two stages have been made. In the first stage, the storage system will only optimise over the regulation capacity and the wholesale market (so no regulation mileage/energy income). The first stage will therefore create the capacity bid. The storage system is then obliged to provide this regulation capacity. This obligation is then fulfilled in the second stage of the model, where the capacity bid cannot be changed, and the storage system will have to provide the regulation demand. However, to keep the state of charge within legal and physical bounds, the storage system will, at the same time, re-optimise over the wholesale market. For clarification figure 5.15 has been made.

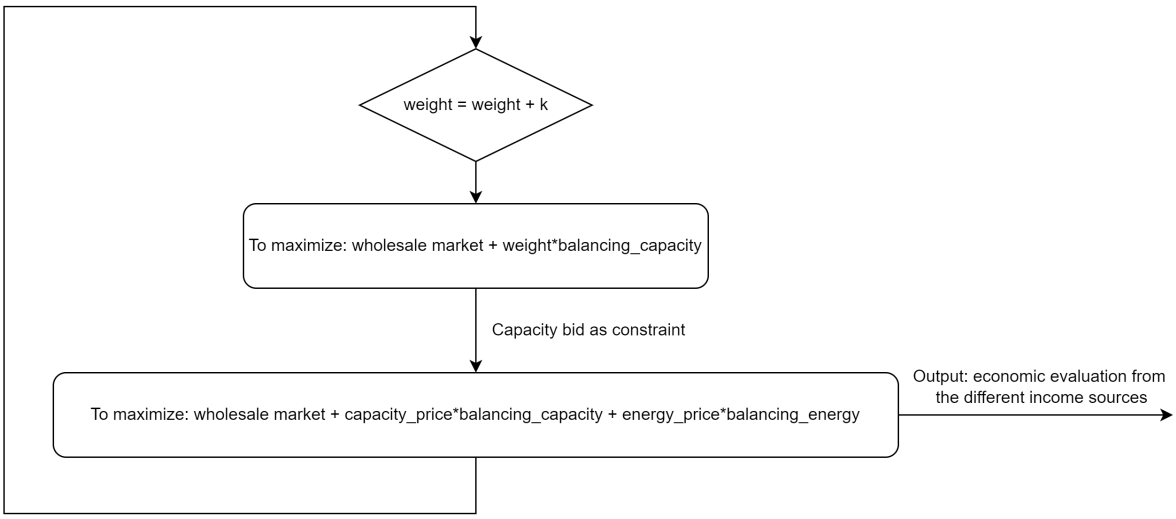

Figure 5.15: Simplified semi-deterministic ULP model overview

The figure shows that the weight factor in front of the capacity decision variables gets incremented every loop by a certain amount. When this happens, the optimisation model will start to favour the balancing market over the wholesale market. In every loop, an economic evaluation will be made, which shows the income from each income source. These sources are the regulation mileage, the regulation capacity and the wholesale market.

Implementation
For the actual simulation, the storage system was set to 15kW with a storage capacity of 105kWh or 7 hours. The self-discharge rate is set to 0.99% per hour, and the efficiency for both charging and discharging is set to 0.99%. The regulation volumes and regulation/wholesale prices have been taken from https://transparency.entsoe.eu/. Since the aFRR data is given every 15 minutes, the same step has been chosen for the simulation. This model has been tested for two different days, one where there is relatively a lot of upwards regulation and a day where the regulation volumes appear more balanced. It should be noted that the regulation volumes are quite unpredictable, and the balanced day should not be used as a proper representation of normal behaviour. The input parameters for the simulation can be seen in Figure 5.16.

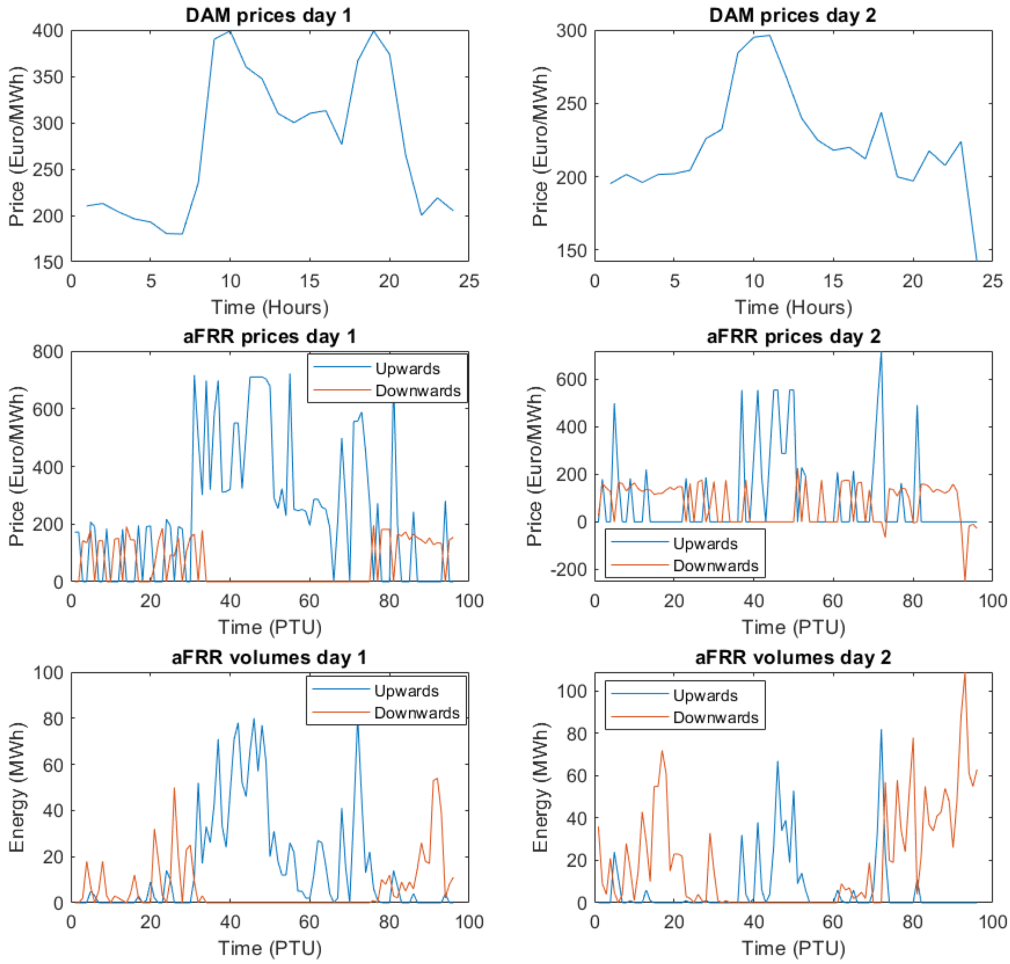

Figure 5.16: Input parameters of two different days, containing DAM prices, and regulation volumes and prices

The high regulation volume day is indicated with day 1, and the more balanced day is indicated with day 2.

Results and discussion
The results in Figure 5.17 correspond to the input parameters with a relatively high upwards regulation. The four plots on the right indicate the storage system behaviour where the capacity weight factor is set to 6. These plots show the state of charge, the charging and discharging on the DAM and aFRR markets, and the aFRR capacity bids, these corresponding to the weight factor of 6. The two plots on the left show the income sources of the storage system for a single day plotted over the changing

capacity weight factor.

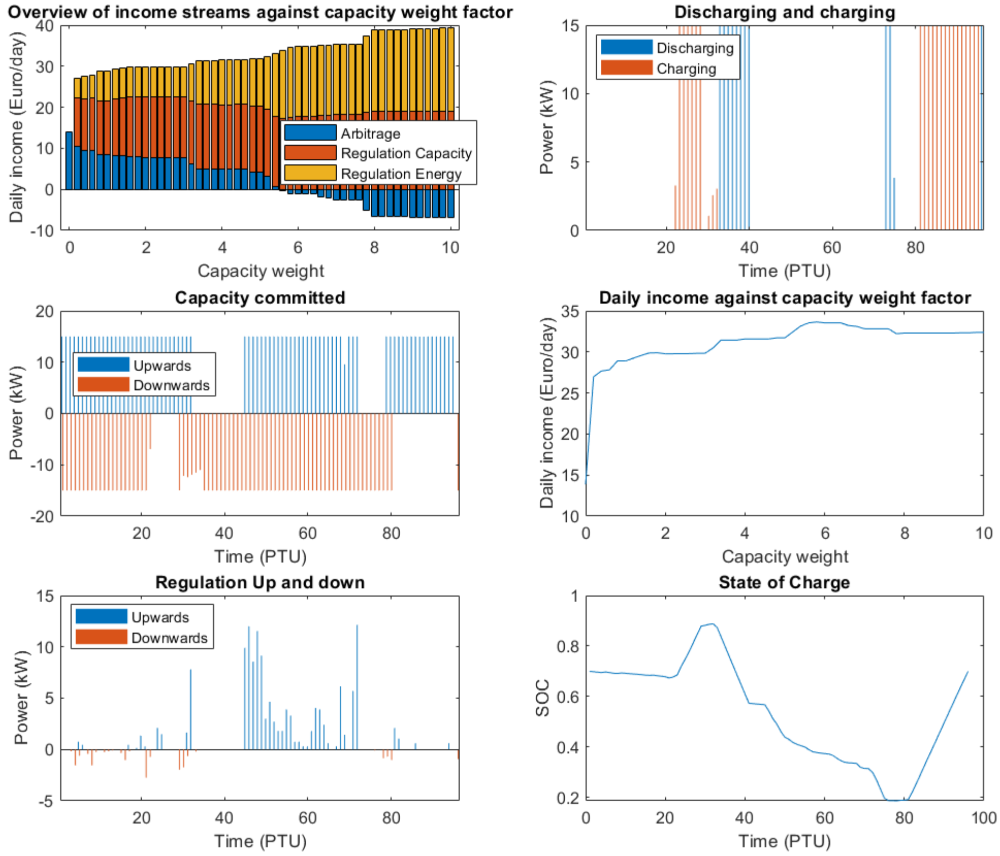

Figure 5.17: Results of semi-deterministic ULP model, fed with the input data from day 1. with the income streams based on changing capacity weight and storage system behaviour when the capacity weight is set to 6

To explain the influence of the weight factor, when this increases, the model will favour allocating capacity to the regulation market over participating in the wholesale market. So for day one, it can be seen that profits increase once the storage system starts participating more in the regulation market. At some point, when this factor keeps increasing, the system reaches a threshold. At this point, the storage system gives up trying to earn money on the wholesale market. Now the system will mostly charge and lose revenue from the wholesale market to commit to the regulation market fully.

Figure 5.18 shows the results when the more balanced day (day 2) is used as input. This figure shows that the storage system loses some income in the energy regulation market for capacity weight factors lower than 0.8. However, this loss is rarely harmful, as down-regulation charges the storage system, and the regulation capacity compensation helps to compensate for this loss. Also, since the storage system can charge from the regulation market, the threshold at which the storage system starts to lose money from the wholesale market comes at a higher capacity weight factor.

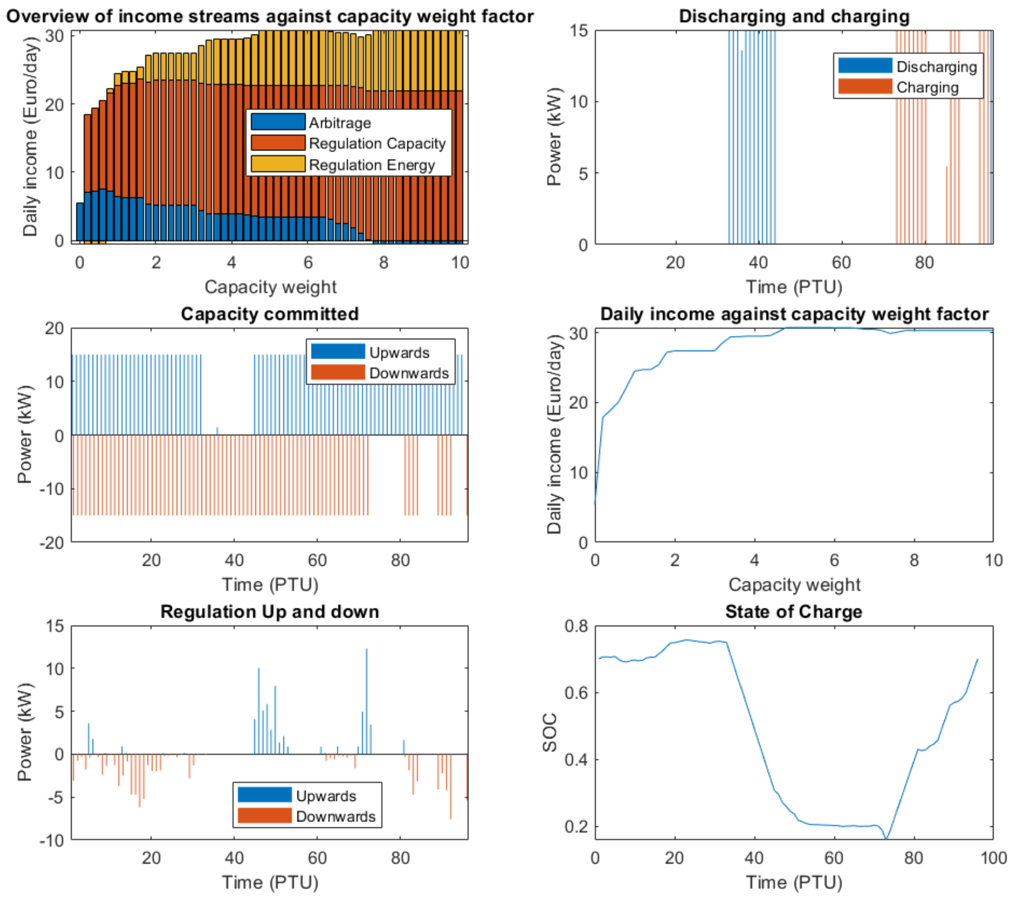

Figure 5.18: Results of semi-deterministic ULP model, fed with the input data from day 2. with the income streams based on changing capacity weight and storage system behaviour when the capacity weight is set to 6

Comparing the deterministic and semi-deterministic model

When comparing Figure 5.17 and 5.14. The difference between the two models can be found in multiple aspects. For this specific day (day 1), the completely deterministic model has a 25% higher income, compared to the semi-deterministic model. This increased income is because the system can better adapt to future regulation mileage. However, in reality, just using the deterministic model is unrealistic and results in a too high valuation of the storage system. The semi-deterministic model has an overall lower income but is closer to reality. However, also this model is not fully non-deterministic since, within the available capacity windows, it is allowed to charge from the wholesale market. Another major difference between the two models is that the deterministic model has a significantly higher revenue stream from specifically the regulation mileage than the semi-deterministic model. This higher revenue can be partly explained by the fact that the deterministic model can specifically choose when to participate on the energy mileage market by adjusting the capacity bids. The semi-deterministic model removes this unwanted freedom.

6

Complete Energy System Model Design

In this chapter, the final completed energy system model will be discussed. The chapter will start with a general overview of the model, followed by more details on how the different markets are implemented and designed, and also is explained why these choices were made. Furthermore, the bidding strategies of both storage systems and generators will be explained. In section 6.2, the system's behaviour was simulated by increasing the total storage capacity. The main goal is to investigate the behaviour and influence of storage systems on different energy markets. The results of the simulations led to recommendations on how to improve European market designs and existing models.

The chapter ends with section 6.4, where a comparison is made between storage systems performing different grid services. So storage systems only performing arbitrage, aFRR or peak shaving. With the objective to compare the impact of different storage services on the energy system model.

6.1. Model overview and design

This section will discuss the design of the complete energy system model. This will be done by first giving an overview of the entire system, and then each part of the design will be further explained. Figure 6.1 gives a simplified overview of the complete model.

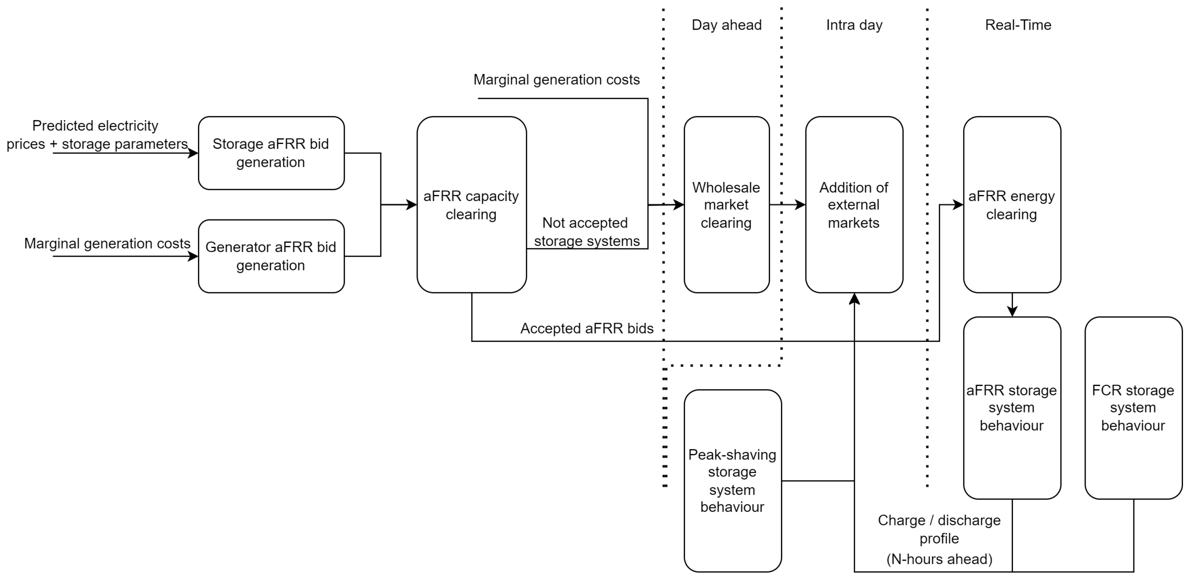

Figure 6.1: The complete energy system model description

As can be seen in the figure, the model is separated into multiple time sections, which also represent the order of operation. The first step is that all the data is loaded. This data exists out of storage system and generator parameters, but also DAM and aFRR demand data. The DAM data is by default perfectly known to the energy storage systems, but this can be adjusted. Using this data, the generators and storage systems will generate bids for the aFRR capacity market. If the storage system is not accepted on the aFRR market, it will participate in the wholesale market. After the wholesale market is cleared, the model moves to the next stage, the intraday section. The intraday market is where the external effects from the different markets like aFRR, FCR and peak-shaving will be added since these charging/discharging needs are determined during operation. For this reason, these needs have to be compensated on the intraday market.

Accepted aFRR bids will be sent to the aFRR energy clearing section. This is where aFRR generation will be matched to aFRR demand. Here both generators and storage systems participate. It can happen that these storage systems that participated in the aFRR market need to charge/discharge on the wholesale market. This contribution, together with the contribution of other markets, will be added to the energy system during the intraday section.

6.1.1. Wholesale market

This subsection will cover the design choices and implementation of the wholesale/day-ahead market. The day-ahead market is implemented using an hourly resolution and simulated with a four-day optimization horizon. The reason this horizon has been chosen is that storage systems will otherwise waste resources in order to meet optimization bounds. To explain, the latest SOC decision variable will either be bound to a specific value or is not bound. If it is bound, the storage system must always end with the specified SOC, and if the decision variable is not bound, it will always completely discharge at the end of the day. For these reasons, if we move this bound three days further, the storage system will behave more optimally.
The generators, which also participate in the DAM, will bid marginally. The reason is that this energy system model assumes a perfectly competitive market.

The storage systems participating in the DAM have been implemented using the same principles as discussed in 5.2.3. So a large storage system will again be split into smaller sub-storage systems. However, in this case, the sub-storage systems will first submit their bids to the balancing market. If these sub-storage systems are not accepted in the balancing market, these will join the day-ahead market and follow the same algorithm discussed in 5.2.3. It is also possible to model a single day using a simpler LLP algorithm discussed in 5.2.2 and subtract the storage systems not participating in the DAM. This has not been done since the information regarding the SOC of the individual storage systems will be lost, and implementing model predictive control (MPC) becomes more challenging.
One addition made to the wholesale market is the implementation of ramping constraints. The ramping constraints are given by equations 6.1 and 6.2. This has been done to make the overall energy system more realistic and open up the market for storage systems to potentially provide ramping support.

$$P^{gen}_{t+1,i} \leq P^{gen}_{t,i} + R_i \qquad \forall t, i \tag{6.1}$$

$$P^{gen}_{t+1,i} \geq P^{gen}_{t,i} - R_i \qquad \forall t, i \tag{6.2}$$

The immediate effect of these newly added ramping constraints is that the electricity price cannot be retrieved by just using the shadow values of the equality constraints since now the price is also dependent on inequality constraints. This means that if no further adjustments were made, the DAM price would become too low when ramping constraints were active. Therefore the electricity price will now be determined by the most expensive active generator.

6.1.2. aFRR

The aFRR market is implemented using two stages, the capacity clearing and the real time regulation energy clearing. In the Netherlands, the upwards and downwards regulation processes are split into two separate clearings, and therefore there will be a total of four unit commitment problems to solve for just the balancing market. An overview of the aFRR process is given in Figure 6.2.

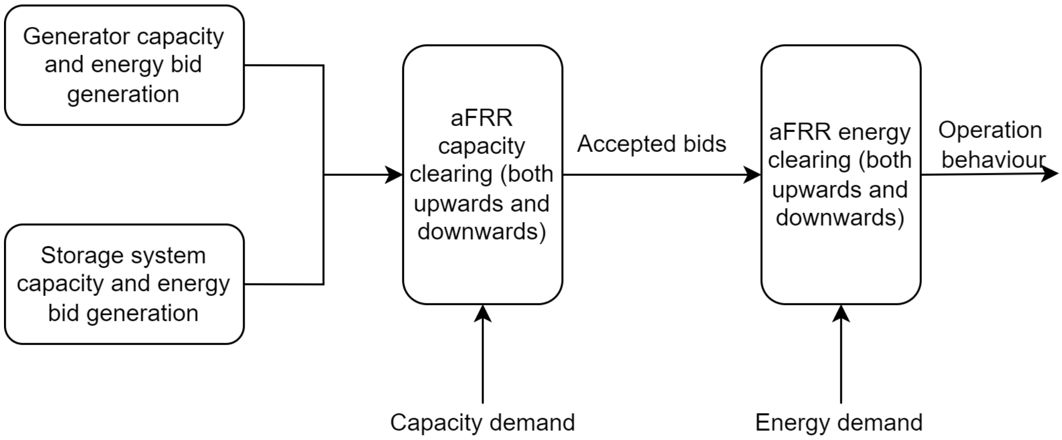

Figure 6.2: The aFRR clearing process visualisation

As seen from the figure, this process is divided into four sub-modules: generator bidding, storage system bidding, capacity clearing and energy clearing. These sub-modules will be further addressed in the following subsections.

Capacity bidding by generators

There are two parameters when it comes to bidding capacity: the amount of capacity in MW the generator can bid and the price per MW. The amount a generator can bid depends on the generator's corresponding ramp rate. For simplicity, the upwards and downwards ramping rates are set to be the same per generator type.

The generators' pricing of the upwards capacity is based on the balancing market theory of the German markets [29]. As discussed in 4.4, extramarginal power plants are generators which are not accepted in the DAM market since these systems have variable costs higher than the DAM price. If these systems were to participate in the balancing market, they need to be actively running to participate. In this model, the price of upwards aFRR capacity by extramarginal power plants is given by equation 6.3.

$$C^{C,up} = (MC^{gen} - P^{dam})\frac{Gen_{min}}{Res^{up}} \tag{6.3}$$

In this equation, $C^{C,up}$ is the cost of upwards capacity in Euro/MW, MC^{gen} is the marginal cost of the generator and P^{dam} is the price of electricity on the DAM. Gen_{min} is the minimal power for which the generator can operate, and Res^{up} is the power that can be committed to upwards regulation.
For infra marginal power plants the capacity costs are given by equation 6.4, which represents the lost profits on the DAM market by reserving the power for upwards regulation.

$$C^{C,up} = P^{dam} - MC^{gen} \tag{6.4}$$

For the downwards regulation, the same principles are applied. For extramarginal power plants, the TSO has to accept expensive generators participating in the DAM to ensure enough down-regulating capacity. These extramarginal power plants are in this version of the model not added in the DAM, but a more realistic system should be added in a future version. The pricing of this capacity is given by equation 6.5.

$$C^{C,down} = (MC^{gen} - P^{dam})\frac{Gen_{min}}{Res^{down}} \tag{6.5}$$

The equation shows that it is very similar to the upwards regulation, as the generator gets compensated for keeping it running.
The intra marginal capacity costs is given by equation 6.6.

$$C^{C,down} = P^{dam} - MC^{gen} \tag{6.6}$$

Hereby it represents the lost profits from the DAM market by having to down-regulate.

In this model, the capacity bidding has been set to an hourly resolution instead of a 15-minute resolution. This is because the bid prices can be based on the DAM prices, which happen to be in an hourly resolution.

It is also possible to modify this system by adding an extra $h * MC$ factor to the capacity bidding process to prevent unfair behaviour. In an oligopoly or monopoly, generators have more freedom when it comes to pricing electricity and can bid their energy for an exorbitant price. However, this extra factor has not been implemented. Mainly because the goal of this model is to simulate a European-like market for which all generators will bid marginal and assume a perfectly competitive market [41].

Capacity bidding by storage systems

Designing the capacity bidding for storage systems allowed for more freedom and challenges. The storage systems participate in the aFRR market differently than regular generators. This is because, in this model, the storage systems are assumed to have high enough ramp rates such that they can fully commit their power to aFRR and, therefore, fully participate in the balancing market or entirely in the DAM market.

In this model is assumed that the storage system has a perfect forecast of the DAM prices and can calculate the potential revenue of the DAM. This is also the primary way the storage systems price their capacity. In the model, the capacity price will be equal to the potential revenue of the storage systems over the 4-day horizon on the DAM. Later this price is then divided equally over the number of hours.

The capacity the storage system can provide is based on the state of charge. Since the storage system cannot down-regulate if the system is completely charged, and storage systems cannot up-regulate when completely discharged. The algorithm used for this is based on the same principles as discussed in 5.2.5. However, the algorithm does not make much sense for storage systems with large storage capacity and little output power, such as redox flow batteries. This is because, for a system rated at 10kW and 120kWh, the system's output power at 0.5 SOC is 5kW, while this could also be 10kW without having too much risk. This is why a parallelogram-like algorithm has been implemented in the final model. The algorithm is visualized in Figure 6.3.

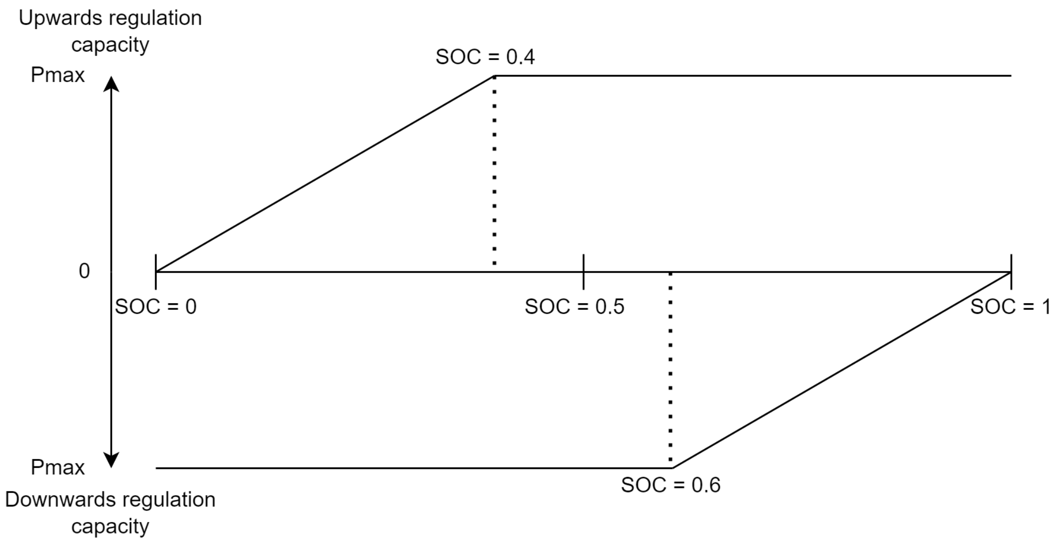

Figure 6.3: Visualisation of algorithm for determining the capacity bid sizes for energy storage systems

As can be seen, when the storage system is fully charged, the down-regulation capacity is set to zero, and the upwards regulation is set to P_{max}, and this is also the case for the congruent scenario. As can be seen, some extra options have been given to the modeller. Namely, the bounds of when the storage system starts to limit output capacity can be adjusted. In this example, these have been set to 0.4 and 0.6.

The current algorithm works in a situation where the efficiency of storage systems is close to perfect.

However, this is seldom the case. Therefore an extra component has been added to the upwards capacity bid size, given as: $P^{C,up} = f(SOC) * \eta^{rte}$ where $f(SOC)$ is the function shown in figure 6.3 and η^{rte} is the round-trip efficiency. By implementing this extra factor, it is ensured that the storage system will remain at roughly the same state of charge after aFRR activation takes place.

The pricing of the storage capacity is also up to some debate, as it is possible for the storage systems to apply multiple bidding strategies. One strategy could be reducing the capacity price to be more likely accepted and then earning revenue from the regulation mileage. This method requires, however, a proper estimation of the potential revenue from the energy aFRR market. One way could be by implementing a simple estimator like introduced in 5.2.5. Since the accuracy of this model is not up to standard, it has been chosen to price the capacity based on the potential DAM revenue. Sometimes the upwards and or downwards capacity does not equal the maximum rated power of the storage system. This means that the price of the capacity should be increased to properly represent the value of potential DAM revenue. The implementation of this can be seen in 6.7.

$$\lambda^{up/down} = \lambda^{pot,dam} \frac{P_{max}}{P^{C,up/down}} \tag{6.7}$$

Here $\lambda^{up/down}$ is the capacity price per MW, $\lambda^{pot,DAM}$ the potential revenue of the DAM per PTU and $P^{C,up/down}$ is the upwards/downwards capacity amount, as determined by the algorithm discussed before in Figure 6.3.

Capacity clearing

The capacity clearing is done by using an optimization based process. There are two main input variables, the capacity market size and the bids from both the storage systems and generators. Hereby minimizing the objective function given in equation 6.8.

$$min \sum_{t=1}^{T} (\sum_{i=1}^{8} \lambda^{C,gen} P_{i,t}^{C,gen,up} + \sum_{j=1}^{50} \lambda^{C,st,j} P_{j,t}^{C,st,up}) \tag{6.8}$$

This is the objective function for the upwards capacity clearing process, but this objective function is equivalent to the downwards capacity clearing objective function. Hereby the goal is to minimize the system's total costs while still meeting the constant capacity demand, which is the constraint described by equation 6.9.

$$\sum_{i=1}^{8} P_{i,t}^{C,gen,up} + \sum_{j=1}^{50} P_{j,t}^{C,st,up} = P^{C,demand,up} \qquad \forall t \tag{6.9}$$

Energy pricing for generators and storage systems

For generators, the pricing for upwards regulation is given by 1.2 times its marginal costs. For downwards regulation, the price is set to 0.9 times the marginal operating costs here. The generator pays the TSO. This bidding strategy originated from the consensus that, in general, generators become less efficient if having to produce more power.

The storage systems energy bidding strategy is based on the current value of the energy. So, therefore, storage systems will bid equal to the electricity price of the DAM. However, to ensure that storage systems make profits, the efficiency factor of the storage systems has to be considered. Therefore the aFRR energy price is given by equations 6.10 and 6.11.

$$\lambda^{E,up,st} = \lambda^{dam} \frac{1}{\eta^{dch}} \tag{6.10}$$

$$\lambda^{E,down,st} = \lambda^{dam} \eta^{ch} \tag{6.11}$$

Without these equations, the storage system would, on average, provide energy for an energy price under the marginal costs.

Energy clearing

The upwards energy clearing process is done by minimizing objective function 6.12 and downwards energy clearing is done by maximizing the function 6.13.

$$min(\sum_{t=1}^{T}(\sum_{i=1}^{8}\lambda^{E,gen}P_{i,t}^{E,gen,up}+\sum_{j=1}^{50}\lambda^{E,st,j}P_{j,t}^{E,st,up})) \tag{6.12}$$

$$max(\sum_{t=1}^{T}(\sum_{i=1}^{8}\lambda^{E,gen}P_{i,t}^{E,gen,down}+\sum_{j=1}^{50}\lambda^{E,st,j}P_{j,t}^{E,st,down})) \tag{6.13}$$

When regulating upwards, activating the cheapest aFRR providers is optimal. Therefore the objective function is to minimise. However, for downwards regulation, it is essential first down to regulate the most expensive aFRR providers. Therefore this objective function has to be maximised instead of minimised.

6.1.3. FCR

From the Entsoe transparency platform website [39], found under the tab ”accepted offers and activated balancing reserves” for FCR. It can be seen that the accepted upwards and downwards capacity is symmetrical, so upwards and downwards capacity is equal. The same is true for the activated units. This is because the bids in FCR are symmetrical, so there are no separate upwards and downwards bids. The data shown is an average of over 4 hours, and the amount of activated frequency regulation is in the range of 17 - 22 MWh, with the most common quantities being 20-21 MWh. Since the average amount of regulated energy remains similar over every PTU, it is possible to approximate the energy demand of FCR as a constant value of 20 or 21 MWh per PTU. The same can be said for the accepted capacity bids.
It is required for a system to participate in the FCR market to at least bid 1 MW. Therefore it is recommended to use multiple storage systems together in order to form a virtual power plant (VPP). Regarding storage control, there is some freedom within the deadband: $f_d = 10mHz$, for which power is not required to be delivered. Using proper control, it is possible for virtual battery energy systems to reach an efficiency of 67.03 % [42].

A study done in 2022 [43], discusses three different methods to recover the state of charge of the storage system. These are:

- To utilize over fulfilment, in which the storage system provides more FCR than requested to recharge.
- To make use of the deadband to choose when to operate when the frequency deviation is within this 10mHz.
- To charge from the intra-day market.

This source introduces a storage system rated 12 MW and 7 MWh, where 11 MW is committed to providing FCR and 1 MW is reserved for charging/discharging on the intraday market. So for making a simpler FCR model, it is assumed that all the charging and discharging is done on the intra-day market and that the factors ”over fulfilment” and ”deadband utilization” can be implemented as an increased efficiency parameter. Participation in the intra-day market can be considered random. Once the storage system hits a softbound, it is obliged to charge to conform to the FCR provision rules. This activation duration is chosen to be hourly, and the frequency of activation is mostly determined by the amount of frequency deviation, which dependents on the geographic location of the storage system.

To illustrate the worst-case scenario of the storage influence on the intra-day market, take a storage system providing FCR with a small storage capacity over power ratio. And assume that this storage system has a 100 MW rating which provides 80 MW FCR (which is almost the entire FCR Dutch market size [39]), and has 20MW reserved for intra-day SOC recovery, then assuming the worst-case scenario the impact would be a constantly flipping signal between the values +20 MW,0 MW and -20 MW which can change every hour. Compared to the overall size of the wholesale market, the FCR impact on the energy system demand and energy prices can safely be neglected.

The revenue streams can be determined by the activated energy amount, for which the activation is pro-rata. This means that the activated energy amount is a scaled value based on the committed FCR capacity. The capacity income is pay-as-bid (still a marginal clearing process). If the storage owner ensures that the bids are accepted. In that case, the storage owner determines the capacity price, thereby ensuring that the storage owner is compensated for the allocated capacity. The maximum size the storage owner can bid is based on the ramping rate of the storage system. According to the Dutch TSO Tennet, the ramping requirement is 30 seconds to fully activate the bid reserve, which is accessible for most small to medium size storage systems [44]. For large-scale storage systems such as pumped hydro, the ramping ability and, therefore, the available FCR capacity is determined by the implemented generator technology.

Discussion of FCR implementation
When it comes to modelling improvements for PyPsa, the hypothesis is that the available storage capacity for other markets is determined by subtracting the available size of the FCR market from the total storage capacity, assuming all systems have proper ramping. However, these market mechanisms and the assumption that the storage system will always be accepted should still be validated in future research and models.

6.1.4. Peak shaving

Peak shaving is a service that can be implemented in multiple ways. For distributed storage systems that provide congestion relief, peak shaving can be modelled as having a fixed shave level for which the storage system has to provide power to comply. It can also be implemented as a system that tries to maximise the peaks shaven. Another way peak-shaving can be implemented is by considering the valleys, which then results in load levelling. Also, the time intervals can differ when trying to maximise peak shaving. This time interval can be on a daily basis but can also consist out of multiple days. The time interval can also be different for each peak shaving storage system.

A study in 2013 [45], illustrates a challenge when it comes to peak shaving. This challenge is that the precise time location of the peaks can be hard to determine. When this forecasted peak data deviates too much from reality, it can cause considerable ramping problems. The optimisation algorithm that is discussed in the paper tries to minimise the bottom and top shave levels using an iterative process, which reduces these levels every loop until the total capacity of the storage system is utilised. A downside of this method is that looping is not computationally favoured since every loop in this algorithm solves an optimisation function.

Another method suggests using a fixed shave profile, for instance, a trapezoidal shave profile. Then the only challenge is finding the exact location of the peak. The advantage of this method is its simplicity, and this is because the only things that can be changed are the dimensions of the trapezoidal shave profile. A downside of this method is that peaks are not perfectly shaven and that the method does not optimally use the complete storage capacity [46].

Implementation
For this model, it is assumed that the goal of the peak shaving algorithm is to minimize the peaks, similar to the model discussed in 5.2.4. The peak-shaving storage model will optimize using a daily interval. It is assumed that the peak shave algorithm of the energy storage system has perfect knowledge of the demand curves.
In practical systems, peak shaving is a case dependent service. A peak shaving storage system can for instance be implemented in a very distributed manner to reduce local congestion. These distributed sections can have very specific peak shaving requirements and diverging demand curves from when compared to the national demand curves. To model all of these specific cases into one single case is challenging, since it requires a model were the power flows and the topology of the energy system are also divined.
However, since the "complete energy system model" tries to model a very large complete energy system, some assumptions had to be made. One is that the sum of all the distributed peak shave systems will result in a uniform single peak shave system behaviour. In reality, this will likely not be the case. For this reason, the implemented peak shave algorithm will only be used as a comparative measure.

A adjustment had to be implemented to the objective function in order to improve the peak shaving results. The change made is that there is now a bottom shave limit added. The reason for this is to make charging more economically efficient and to prevent rapid ramping which could be seen in the older version of the peak shave algorithm (Figure 5.8). The new objective function is given by equation 6.14.

$$minL^{shaveup} - L^{shavedown} \tag{6.14}$$

Where $L^{shaveup}$ is the top shave level and $L^{shavedown}$ is the bottom shave level. The storage system optimizes these levels and ensures that the new demand stays between these shave levels for each daily time interval.

6.2. Energy system simulation with increasing storage capacity

The following subsections will investigate the normal operation behaviour of the complete energy system model based on redox flow battery technology. This will be done by increasing the total storage capacity from 0 to 500 MW. Hereby will be looked at the storage influence on both the DAM and the aFRR market. Each subsection discusses the results of the operation behaviour of the model. Lastly, this section ends with a simulation and discussion regarding the operation of a Li-ion storage system.

6.2.1. Implementation

In table 6.1 the parameters describing the energy system are given. There are a total of eight generators, consisting of four gas plants (OCGT 1 and 2, CCGT 1 and 2), two coal plants (COAL 1 and 2) and two nuclear plants (NUCE 1 and 2).

Generators/Storage Systems:	OCGT_1	OCGT_2	CCGT_2+1	COAL_2+1	NUCE_2+1
Capacity (MW):	1645	645	645	495	700
Variable Costs (Euro/MWh):	255	210	175/140	105/70	35/0
Minimal operating power (MW):	822.5	322.5	258	247.5	700
Ramping rate (%/5min):	8.3	8.3	8.3	3.3	0.01

Table 6.1: System parameters of the complete energy system model

This system has been simulated using scaled data from the entsoe transparency platform of the dutch markets. This data only consists of aFRR demand and general DAM demand.

6.2.2. Results of operation without energy storage

The following figures (6.4,6.5 and 6.6) show the operation of the current energy system without any storage components. In Figure 6.4, the DAM behaviour of the energy system simulated over four days can be seen. In the left plot are the results of the energy clearing process. The coloured bars represent the power provided by each separate generator. The DAM price over time is seen in the right plot.

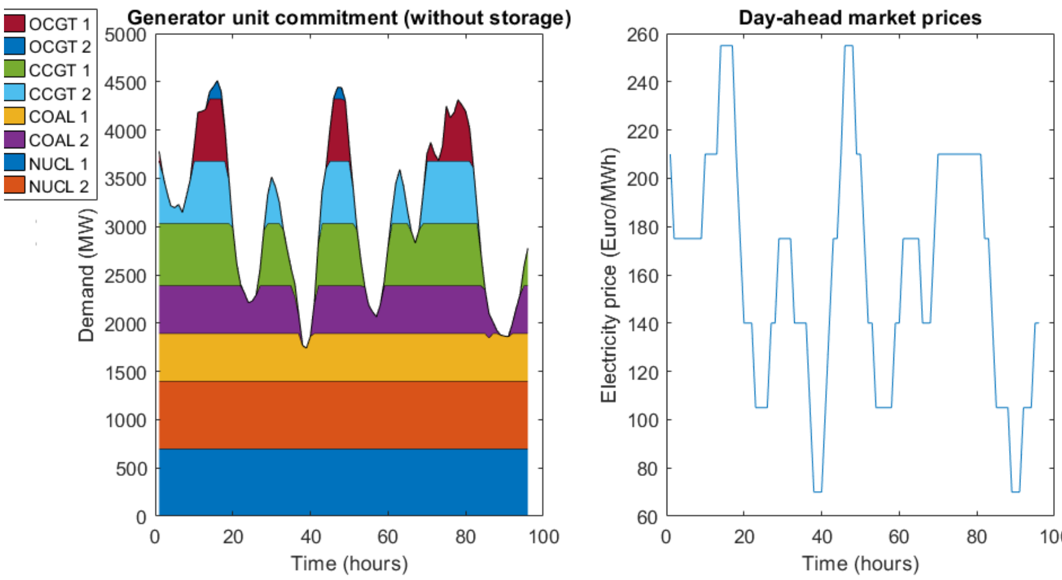

Figure 6.4: DAM simulation of the complete model without implementing storage over 4 days

The capacity clearing process is seen in Figure 6.5, the accepted generators are shown in the left plots for both upwards and downwards regulation. Also, the plots on the right side of the figure show the most expensive accepted generator for that specific time interval. It should be noted that the generators only get compensated for the bid they made and not the most expensive accepted bid, since there is a pay-as-bid rule for capacity.

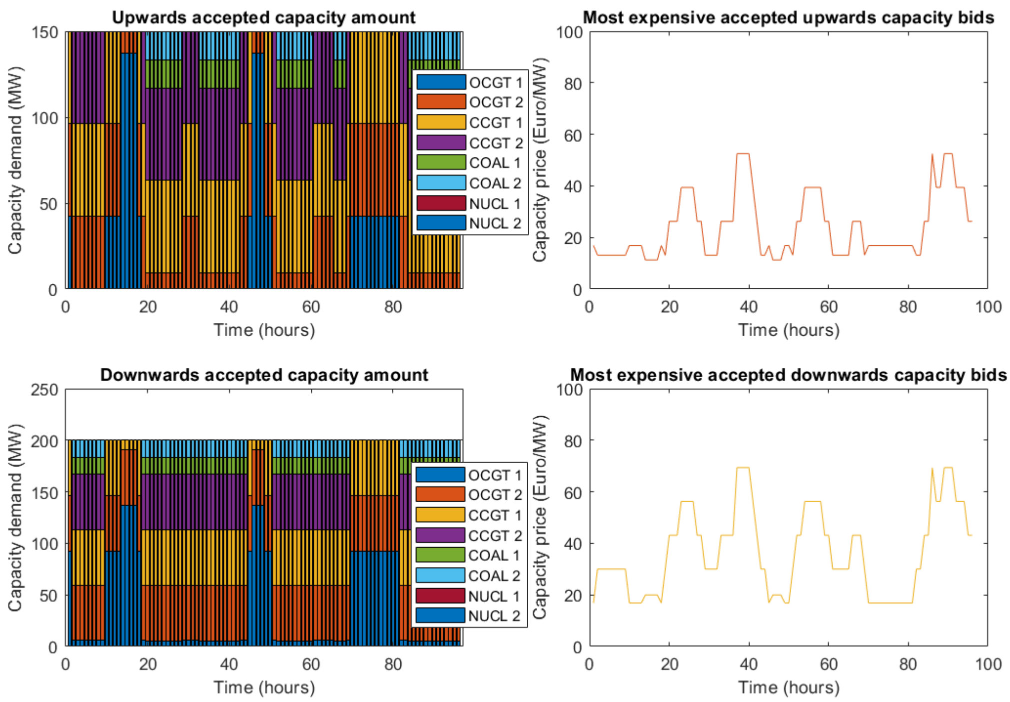

Figure 6.5: aFRR capacity clearing simulation results of the complete model without implementing storage over 4 days

The aFRR energy clearing was simulated for one day, with a 15-minute resolution (one PTU). Figure 6.6 shows the results of the energy clearing. Here the colours represent which generator is active.

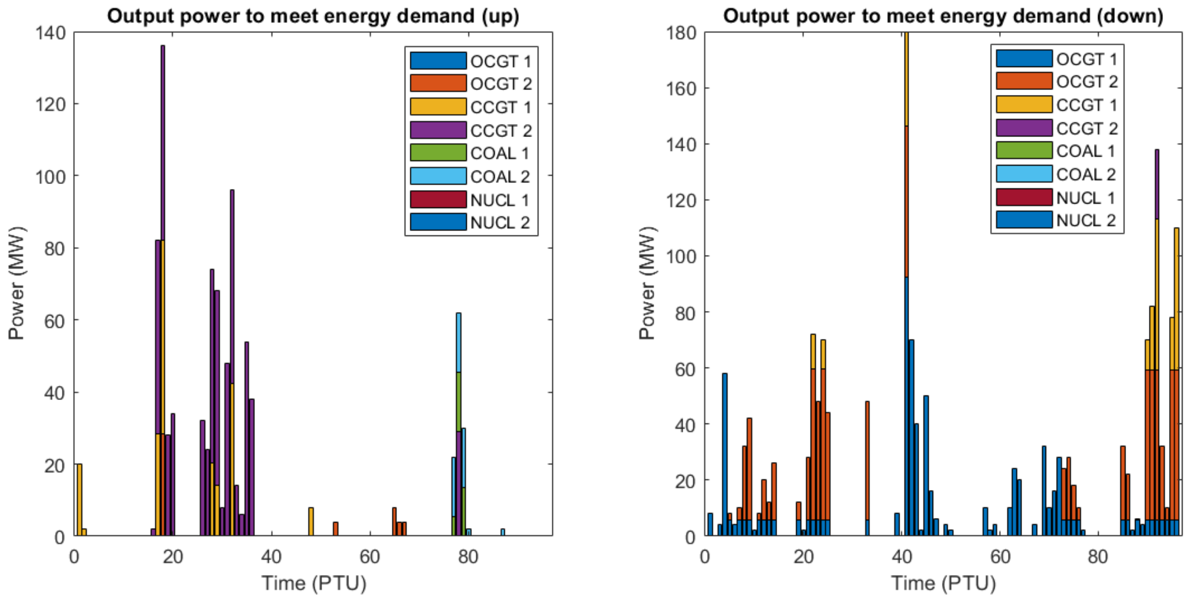

Figure 6.6: aFRR energy clearing simulation results of the complete model without implementing storage over a single day

Discussion of energy system with no energy storage
Figure 6.4 shows the clearing of the DAM market, which is cleared for four days by only using the thermal generation units. Unlike the previously discussed models, the electricity price of the complete energy system model can no longer be entirely determined by the shadow prices of the equality constraints. For most time intervals using the shadow price is completely fine. However, for the time intervals where the ramping constraints bound the objective function, using the equality constraints no longer works since the ramping constraints are implemented as an inequality constraint. Therefore the electricity prices now have to be determined by the most expensive active generator. The effect of the ramping constraints can be seen around areas where the demand change is relatively significant. Here can be seen that multiple generators reduce or increase output at the same time.
The capacity clearing process, as seen in 6.5, ensures the cheapest bids are accepted. From the figure can be seen that the cheapest bids do generally not come from cheap nuclear fuel generators but actually from generators that have variable costs close to the DAM prices. This is because the revenue from the DAM is determined by the DAM price minus the marginal cost of the generators. Therefore, these systems can bid their capacities at prices close to zero. Since coal plants cannot bid as much capacity due to their limited ramping capabilities, it is necessary also to accept a lot of regulation capacity from gas generators.
The last figure (Figure 6.6) shows the aFRR demand being fulfilled by the generators. This figure shows a single day of operation, and as can be seen, the only generators allowed to participate are the ones accepted in the capacity clearing process. In the left plot, the upwards energy clearing is done. It can be seen that, out of the accepted capacity bids, the generators with the lowest marginal costs will be employed. For the right plot, the opposite is the case. Here the generators with the highest marginal costs will be downregulated first. Overall this operation is as expected and will result in the lowest overall energy costs.

6.2.3. Operation of system with 100MW of energy storage

In this section, the same system will be simulated but this time with 100 MW of energy storage. The implemented storage systems are based on redox flow battery technology, a storage technology discussed in 3.2.2. The complete list of parameters is given in table 6.2. The starting state of charge is set to 0.5 for all storage systems. This allows for the highest participation in the aFRR market.

Parameters	Quantities	Units
Rated power	100	MW
Storage capacity	1000	MWh
Round trip efficiency	75	%
Charge efficiency	86.60	%
Discharge efficiency	86.60	%
Self-discharge rate	0	% / day

Table 6.2: The energy storage system parameters representing a 100 MW redox flow battery

Results of 100MW of storage

This amount of storage capacity did not influence the DAM market since every single storage system is accepted on the regulation market, and no charging was needed. Therefore, the DAM results are not shown since these are the same as in the zero storage capacity case. The capacity clearing results are seen in Figure 6.7 shows the capacity clearing.

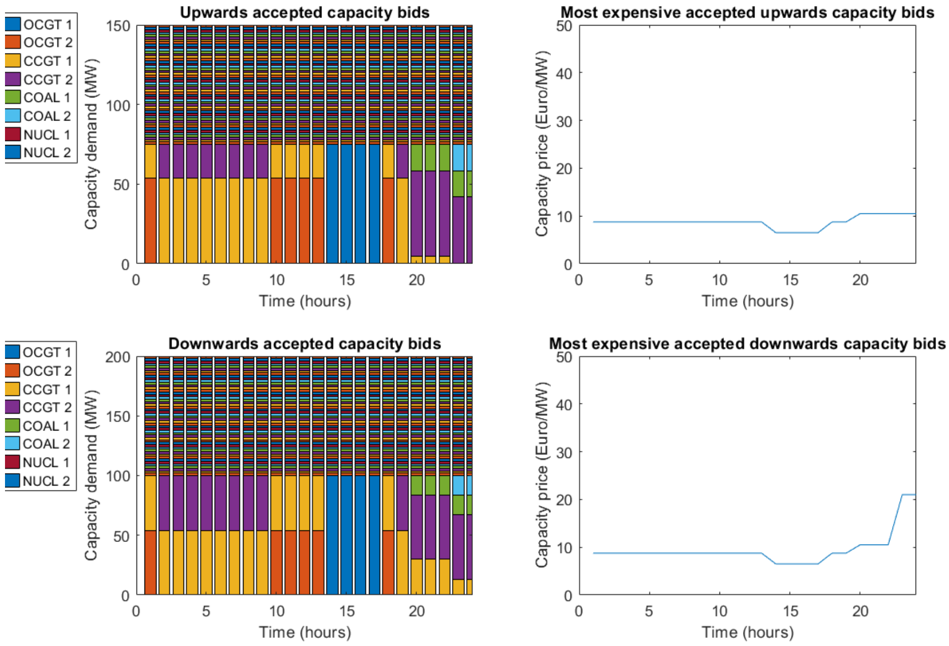

Figure 6.7: aFRR capacity clearing simulation results of the complete model with 100MW of storage capacity of a single day

Figure 6.8 shows the energy clearing process. In this figure, the plots on the left show the complete system committing to aFRR demand and the contribution of solely the storage systems on the right.

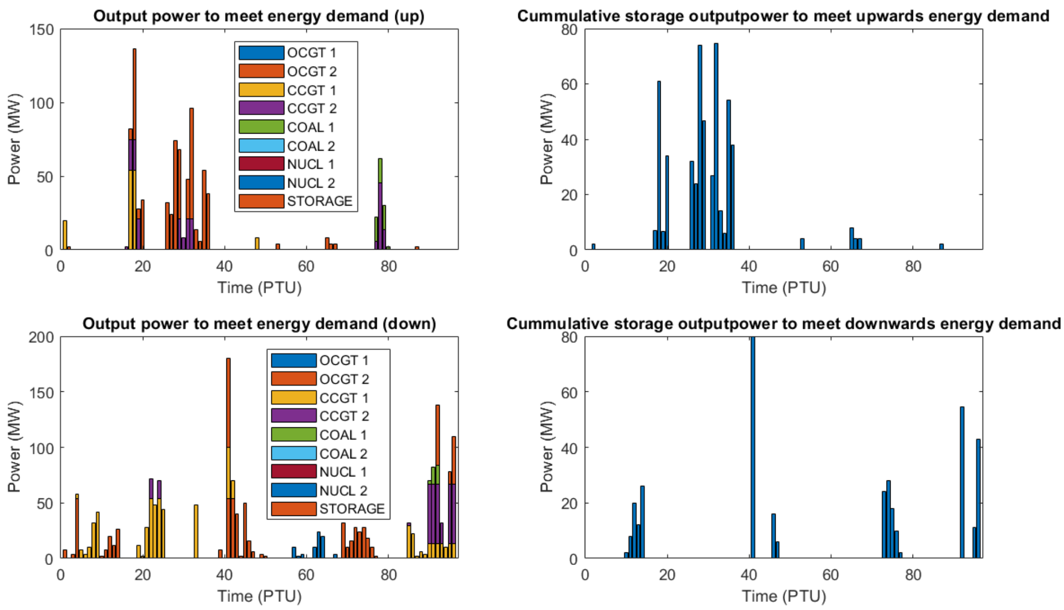

Figure 6.8: aFRR energy clearing simulation results of the complete model with 100MW of storage capacity of a single day

In Figure 6.9, the same system has been simulated with randomized stored energy. The state of charge can range from 0 (completely discharged) to 1 (completely charged). The storage system still does not influence the DAM market, and the total downwards and upwards capacity is 82.41 MW and 56 MW, respectively.

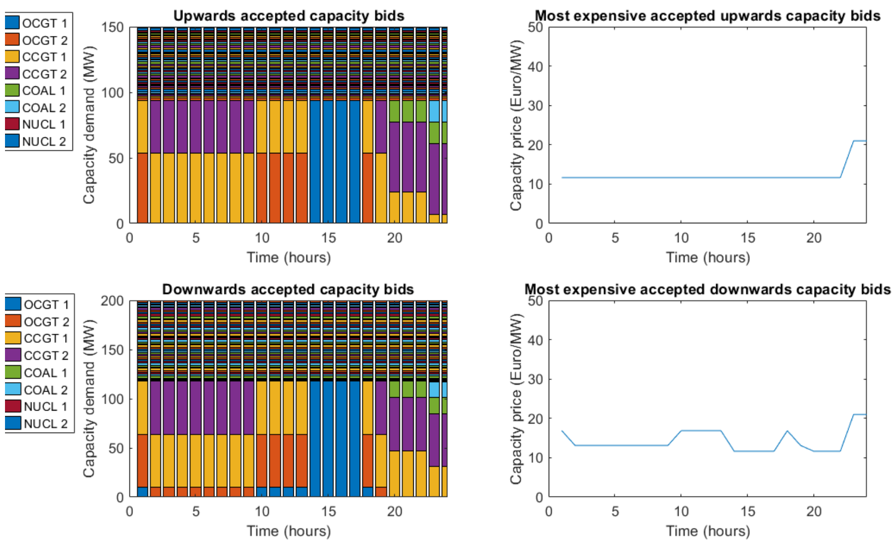

Figure 6.9: aFRR capacity clearing simulation results of the complete model with 100MW of storage capacity of a single day, with random starting energy

Discussion of 100MW storage

As can be seen from the first figure (Figure 6.7), the storage systems commit 100 MW of downwards capacity and 75 MW of upwards capacity. This results from the added round trip efficiency factor introduced in 6.1.2. If this factor were not there, the storage systems would be required to charge from the DAM. Another way to increase the probability of having to charge on the DAM is by decreasing the energy storage capacity or changing the soft bounds. These changes have an effect that the chance of violating the soft bounds becomes larger than with larger storage capacities.

Figure 6.8 shows the energy clearing, and now it can be seen how the storage system participates. As can be seen, the storage system does not always get accepted. This is mainly because the storage system bids at the DAM price, and it can regularly happen that accepted generators have lower marginal costs. This is why these cheaper generators can be prioritized over storage systems.
The current behaviour is not natural since this scenario assumes that all the storage systems started at the same state of charge of 0.5. If the simulation is to be done again with random states of charge like in Figure 6.9, then the total available aFRR capacity by storage systems will decrease, and therefore the capacity prices will increase. The decrease in capacity can be explained by the fact that in the previous case, storage systems were able to bid fully upwards and fully downwards, and in the current scenario, this is no longer possible. The reduction of the available aFRR capacity is dependent on the random starting states of charge. However, the reduction in downwards and upwards capacity is generally between 17% and 22% respectively.

6.2.4. Operation of system with 250MW of energy storage

In this scenario, the same storage system technology is tested. However, the total rated power is now set to 250 MW with 2500 MWh of stored energy, the same power over storage capacity ratio as used in the 100 MW case.

Results of 250MW of storage capacity

In Figure 6.10 the aFRR capacity clearing results can be seen. And in Figure 6.11 the DAM clearing process can be seen, with shown in yellow the influence of the regulation mileage (which is barely visible) and in the brown colour, which is filling the peaks and the valleys, are the storage systems which are participating in the DAM.

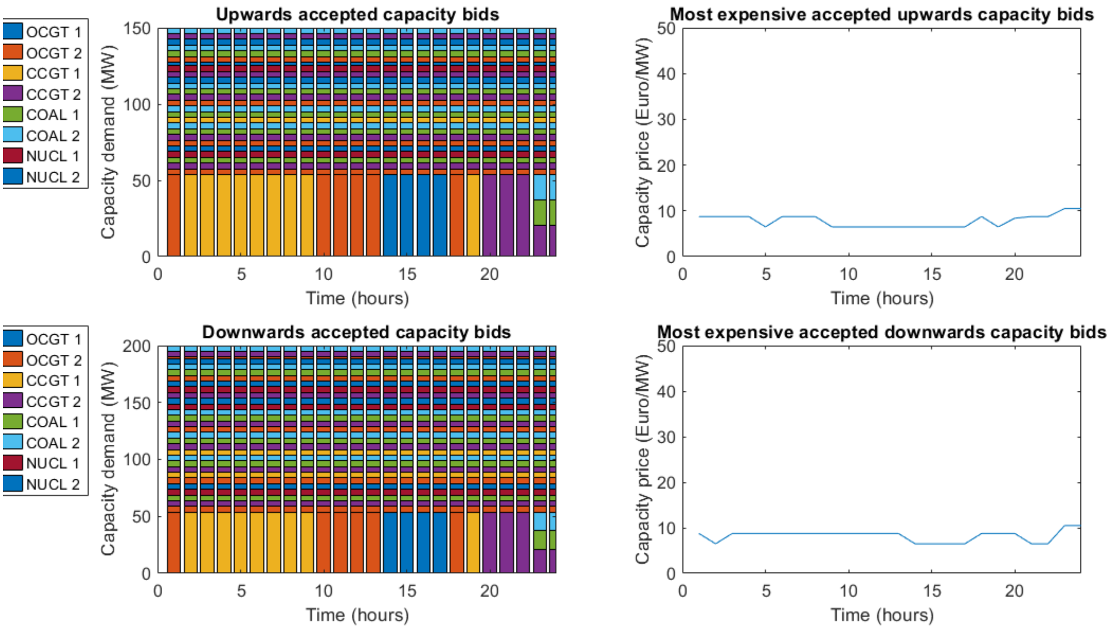

Figure 6.10: aFRR capacity clearing simulation results of the complete model with 250MW of storage capacity

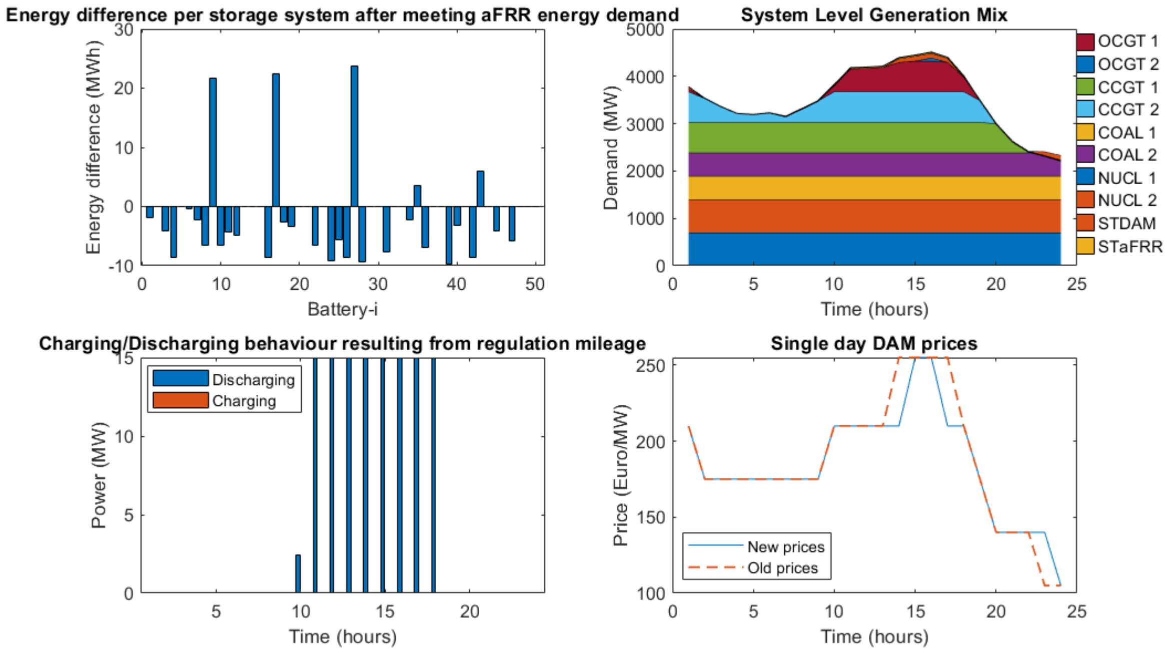

Figure 6.11: Individual storage system responses, aFRR recharge/discharge behaviour, DAM participation and influence on DAM prices

Discussion of 250MW of storage capacity

As can be seen, this is the moment some storage systems are only accepted for downwards regulation. This resulted in too much-stored energy, which must be discharged to stay within normal operation bounds. Currently, this discharge is relatively tiny and barely visible on the ”System level generation mix” plot in Figure 6.11. Since some storage systems cannot join the aFRR market anymore, they join the DAM, and this influence is noticeable as it also starts to impact the DAM prices by levelling them.

6.2.5. Operation of system with 500MW of energy storage

In this scenario, the same storage system was simulated again, but with 500 MW of power and 5000 MWh of storage capacity.

Results of 500MW of storage capacity

Figure 6.12 shows the influence of 500 MW storage capacity on the capacity bidding process. Figure 6.13 shows the storage system behaviour in more detail, as it shows the individual stored energy differential, influence on the generation mix, charging and discharging behaviour and the influence on the single day DAM prices.

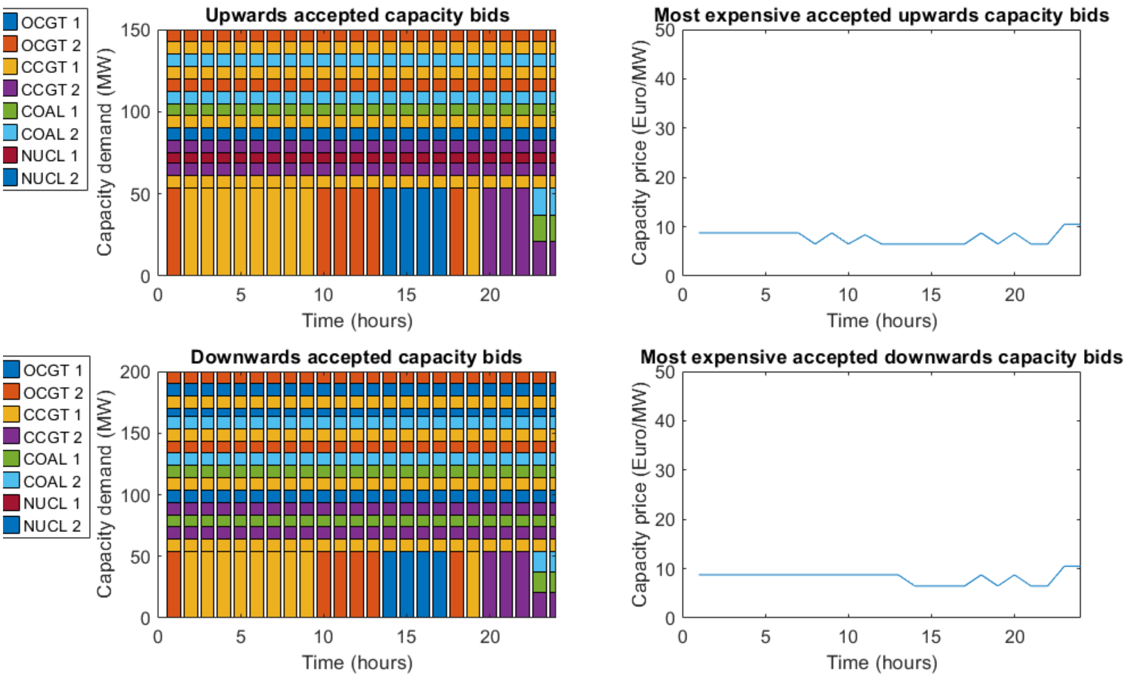

Figure 6.12: aFRR capacity clearing simulation results of the complete model with 500MW of storage capacity

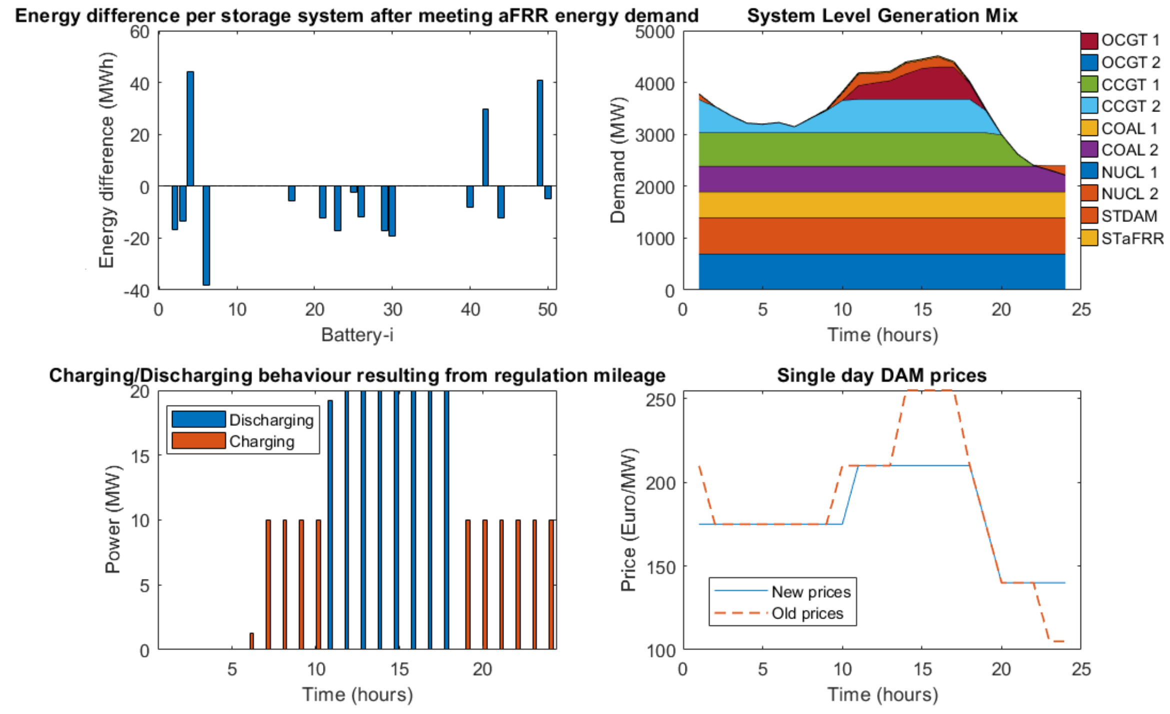

Figure 6.13: Individual storage system responses, aFRR recharge/discharge behaviour, DAM participation and influence on DAM prices

Discussion of 500MW of storage capacity

As shown in Figure 6.12, the total aFRR market penetration remains the same as the prices. This is because the aFRR market is saturated, and the extra storage systems cannot compete with the generators bidding their capacity at 0 Euro/MW. In Figure 6.13, the influence of the storage system on the DAM starts becoming significant, resulting in significant changes in electricity prices. What also can be seen is that the influence of the aFRR participation remains small. Some of the participants in the intraday market (storage systems having to charge due to aFRR participation) are not accepted by both upwards and downwards markets. So these are storage systems that can only up or down-regulate.

6.2.6. System with 350MW of lithium-ion storage technology

This simulation was done with a 350MW lithium-ion storage system, implemented with the following parameters shown in table 6.3.

Parameters	Quantities	Units
Rated power	350	MW
Storage capacity	1400	MWh
Round trip efficiency	98	%
Charge efficiency	99	%
Discharge efficiency	99	%
Self-discharge rate	2	% / day

Table 6.3: Lithium-ion storage parameters used in the 350 MW normal behaviour simulation

In this scenario, the round-trip efficiency is significantly higher, but with the drawback that there is now a larger self-discharge rate and a smaller storage capacity since the storage over power ratio is 4. It should be noted that for practical Li-ion storage systems, the round trip efficiency is much lower due to necessary power conversion.

Results of 350MW lithium-ion storage

In the figures 6.14, 6.15 and 6.16 the results of the simulation are plotted.

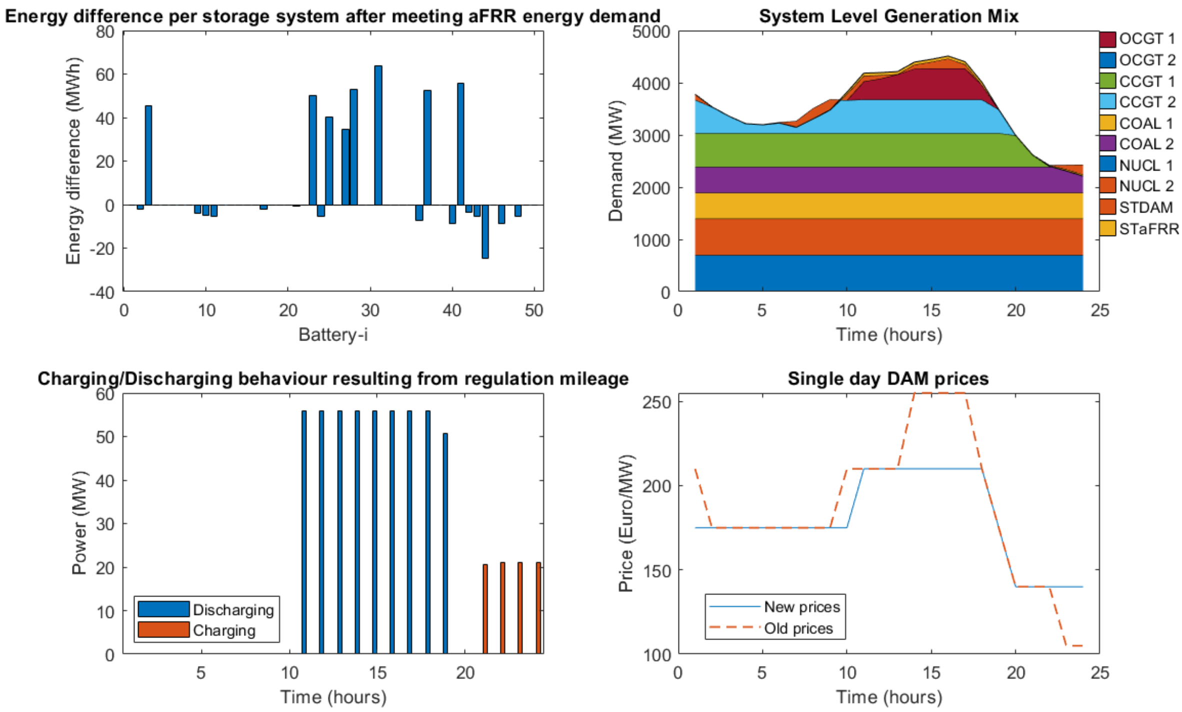

Figure 6.14: Individual storage system responses, aFRR recharge/discharge behaviour, DAM participation and influence on DAM prices

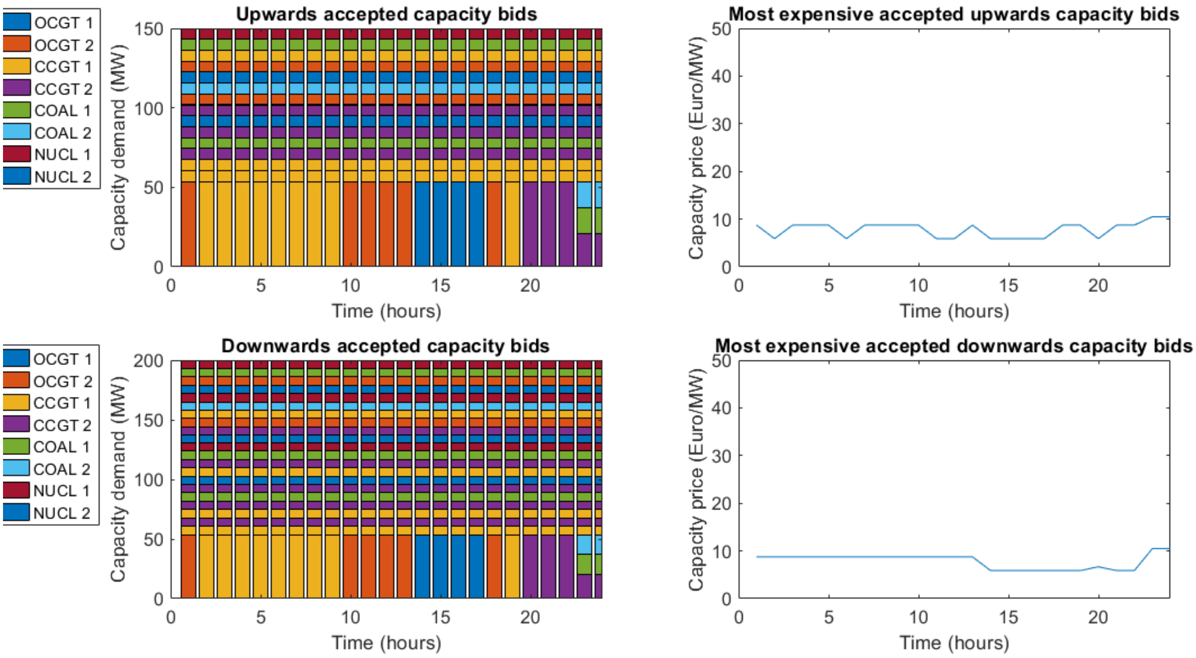

Figure 6.15: Capacity clearing results (left) with most expensive accepted capacity bids (right) for both upwards and downwards capacity bids

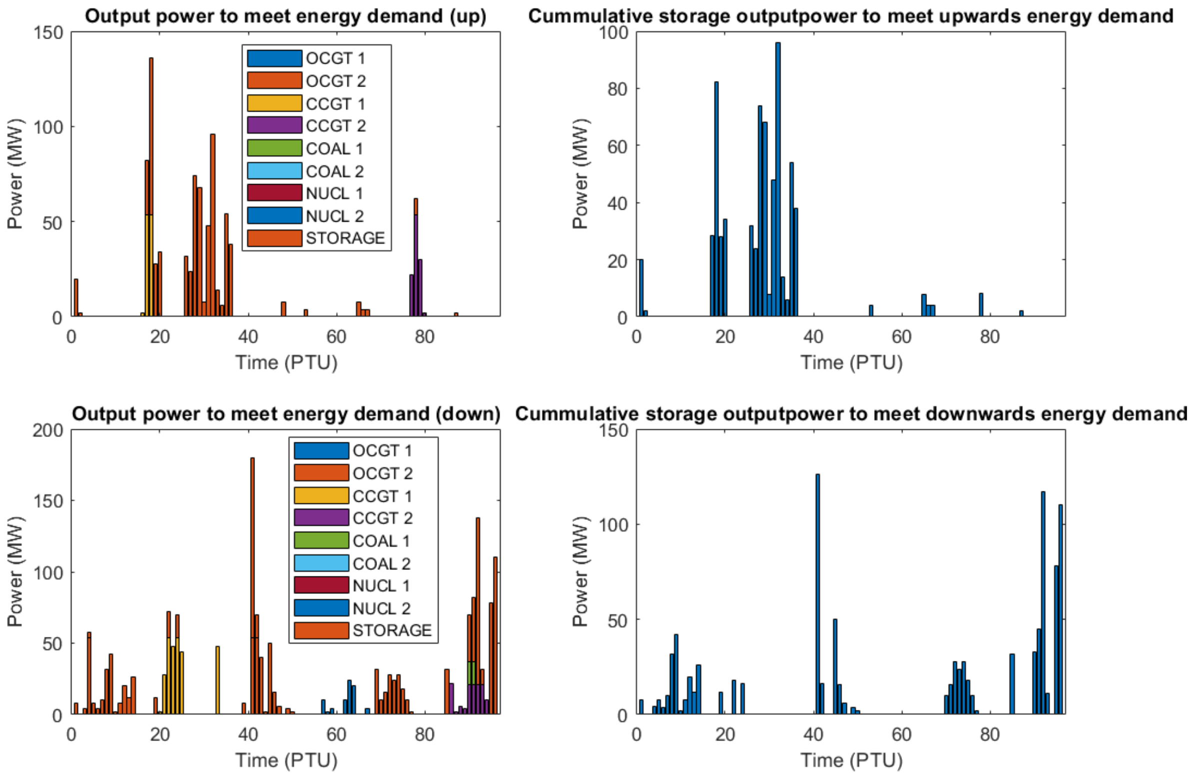

Figure 6.16: aFRR energy clearing results, with the complete system response on the left and only the storage system participation on the right

Discussion of 350MW lithium-ion storage
In Figure 6.14 can be seen that the Lithium-ion storage systems violate SOC boundaries due to the regulation mileage, which is seen in the top-left plot. These systems were accepted on the downwards capacity market and not entirely on the upwards market and also the other way around. This resulted in having to charge/discharge on the DAM, which can be seen as the thin yellow area on the top right plot and the bottom left plot. Furthermore, not all storage systems were accepted on the aFRR market, which meant that there was also DAM participation. This can be seen as the dark orange in the top right plot, which resulted in the price changes in the bottom right plot.

Since the efficiency of these storage systems is quite high, the chance of being cleared due to the energy clearing process also becomes higher. This can be seen when comparing Figure 6.16 with Figure 6.8. This is because the more efficient lithium-ion storage systems can bid their energy closer to the DAM price. However, a negative side effect is that these systems are so often activated and the storage capacity is lower, that the chance of violating SOC boundaries becomes much larger.

Figure 6.15 shows that the capacity market participation is very similar to the previous simulations and that it saturates at a certain point. The saturation of the aFRR capacity market will happen later in reality. In the model, this saturation happens when the capacity markets are filled by 75% and 66%, but in real-world systems, this saturation will probably be closer to 100%. This is because the current system only has eight generators, with one of each operating at the DAM price. This implies that this generator has bid its capacity at a price of 0 euro/MWh. In reality, there are many more generators and bids resulting in more nonzero capacity bids, which will give the storage systems more opportunities to participate in this market.

It is crucial to note that practical Li-ion storage systems cannot realise the 98% efficiency due to the need for power conversion modules, which will significantly reduce the total energy storage system's efficiency.

6.3. Model Predictive Control

A commonly used way to handle optimisation uncertainties is using model predictive control (MPC) algorithms, which is a method that combines uncertainty modelling and optimisation to optimise over a moving horizon [47]. This means that the MPC optimisation model recalculates the optimal solution at every time interval based on updated input data.

The ”complete energy system model” described in this chapter has some potential sources of uncertainty. The first can be introduced by inducing an error in the DAM demand forecast. The second source of uncertainty comes from the aFRR activation since the exact required aFRR activation is nearly impossible to determine. Therefore it was necessary to implement some form of MPC.

6.3.1. Implementation of MPC

MPC is implemented using a 4-day moving horizon for the DAM. The storage system can optimize the dispatch over these four days and make daily bids on the aFRR market. After a day of operation, the aFRR activation has introduced a change in the SOC of some storage systems. Every day all the SOCs are updated based on aFRR and DAM activation. Using the new SOC, the horizon moves one day and the storage system re-optimizes the dispatch.

In the earlier versions of the model, implementing MPC resulted in unwanted behaviour, namely that the storage systems which participated in the DAM could have a SOC below the soft limits set by the aFRR algorithm. This resulted in some previously DAM participating storage systems would be forced by the algorithm to charge/discharge. Also, storage systems would bid very small capacities, resulting in many accepted aFRR bids, making the DAM participation nearly zero.

So some measures had to be taken to avoid this unwanted behaviour. Firstly, it is no longer possible to bid capacity upwards if the SOC is less than 0.2, and it is no longer possible to bid capacity downwards if the SOC is over 0.8. This does mean that these storage systems can still participate in the opposite market (upwards/downwards). The second measure taken is those storage systems entering the aFRR algorithm while having $0.2 > SOC$ and $SOC > 0.8$ are no longer immediately activated to recover the SOC since now they are only active for one direction.

For the simulation, the storage system described in table 6.4 was implemented.

Parameters	Quantities	Units
Rated power	300	MW
Storage capacity	3000	MWh
Round trip efficiency	75	%
Charge efficiency	86.6	%
Discharge efficiency	86.6	%
Self-discharge rate	0.02	% / day

Table 6.4: Storage parameters implemented for the MPC modelling

6.3.2. Results of MPC

In Figure 6.17 the system behaviour is plotted, and in Figure 6.18 the changes to the DAM prices and aFRR discharge/charge behaviour on the DAM is seen.

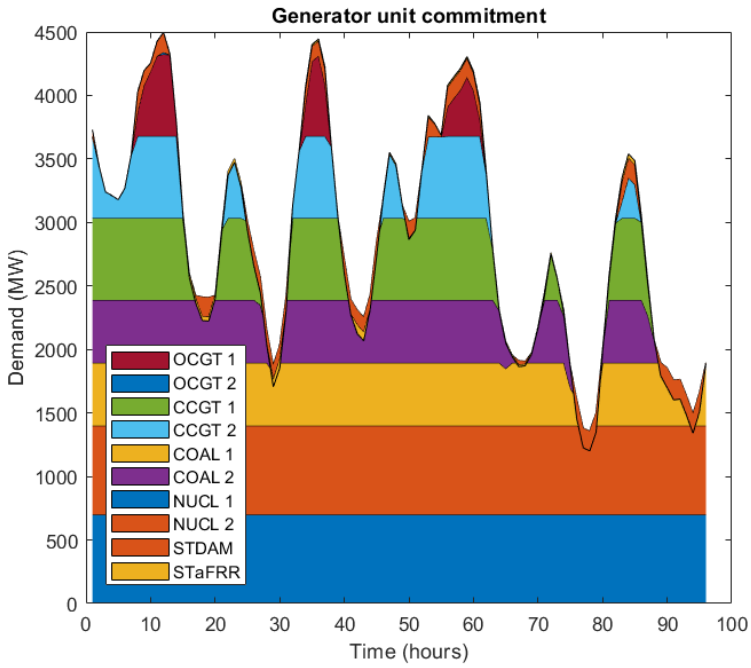

Figure 6.17: The energy clearing results when implementing a 300 MW storage system using MPC, with DAM and aFRR participation

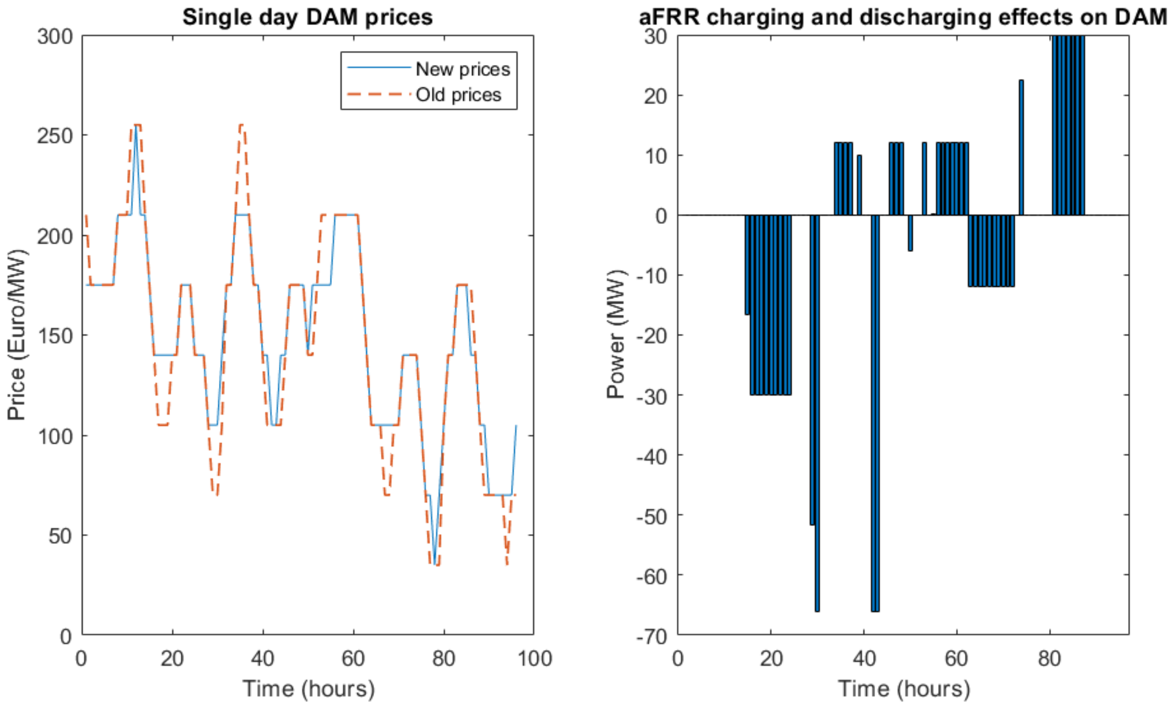

Figure 6.18: The DAM price changes and aFRR charging and discharging behaviour when a 300 MW storage system using MPC is implemented

6.3.3. Discussion of MPC

Figure 6.17 shows the real-time operation of the energy system using MPC. Using the implemented measures, the behaviour of the system remains stable. The DAM participating storage systems do not massively join the aFRR market and vice versa.

An interesting thing to notice is the arbitrage storage behaviour between hours 25 and 27. The storage system discharges at a time when no peak is present. This behaviour is due to the ramping constraints, which have temporally increased the price, making it attractive for storage systems to participate. This unintentionally results in a storage system providing ramping support.

A downside of this model is that the required simulation time is increasing. The 4-day simulation took 30 seconds, which means that simulating a year would cost roughly 45 minutes. However, it should be taken into account that, currently, not many time-optimization strategies have been implemented. Therefore, the simulation time can be further reduced if that is wanted. However, it is still recommended that the recommendations discussed in 6.5 are followed for longer time intervals.

6.4. Comparing grid applications

In this section, three separate simulations are done with the same set of storage systems. Here the main difference between scenarios is the function of the storage systems. So the storage systems will be only trading on the DAM, only participating on the aFRR market or just performing peak shaving services.

6.4.1. Implementation

For this simulation, storage related parameters were changed. These parameters are summarised in Table 6.5. Furthermore, the upwards and downwards aFRR capacity market size has been set to 225 MW and 300 MW, respectively. The aFRR demand has doubled. This exaggerates the influence of the aFRR market and allows for a clearer look at the influence of aFRR.

Parameters	Quantities	Units
Rated power	225	MW
Storage capacity	2250	MWh
Round trip efficiency	75	%
Charge efficiency	86.6	%
Discharge efficiency	86.6	%
Self-discharge rate	2	% / day

Table 6.5: Storage system parameters for the specific application modelling

6.4.2. Results of storage systems performing arbitrage, regulation and peak shaving

In order to simulate this scenario, the capacity price bids of the storage systems were set very high such that they could not be accepted. The price changes and unit commitment results are plotted in Figure 6.19.

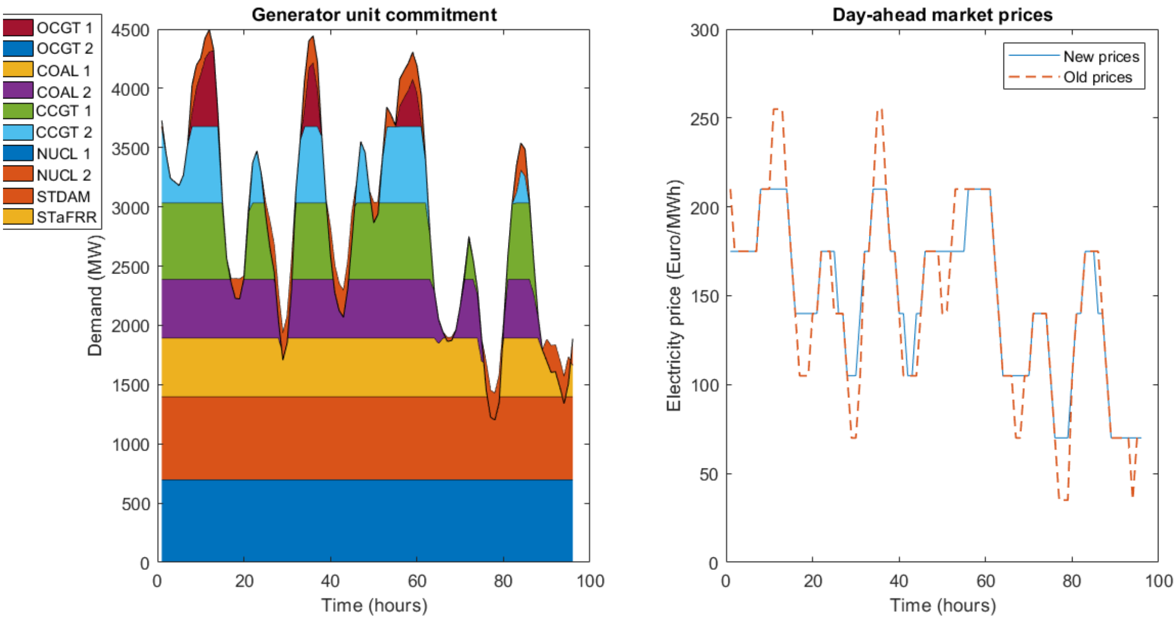

Figure 6.19: The behavior of a 225 MW storage system only able to participate on the DAM, with the generation mix on the left plot and the influence on the DAM prices on the right

The storage behaviour is seen as the orange colour filling the peaks and valleys. The right side of the figure shows the electricity price before and after adding storage.

Figure 6.20 shows the influence of storage systems having to charge and discharge on the DAM due to aFRR behaviour. Figure 6.21 shows the aFRR storage system behaviour in more detail and the influence on the electricity price.

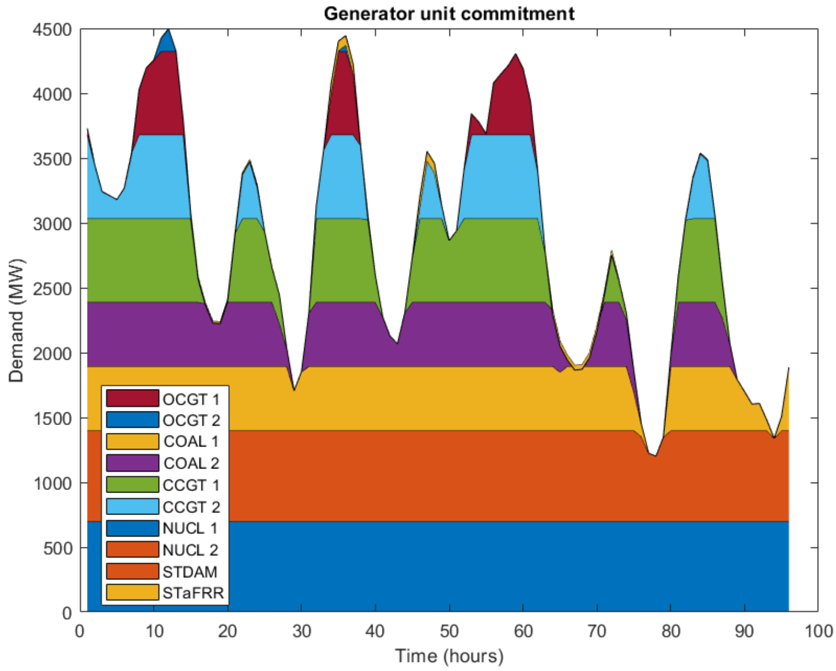

Figure 6.20: System level behaviour of 225 MW storage system only able to participate on the aFRR market

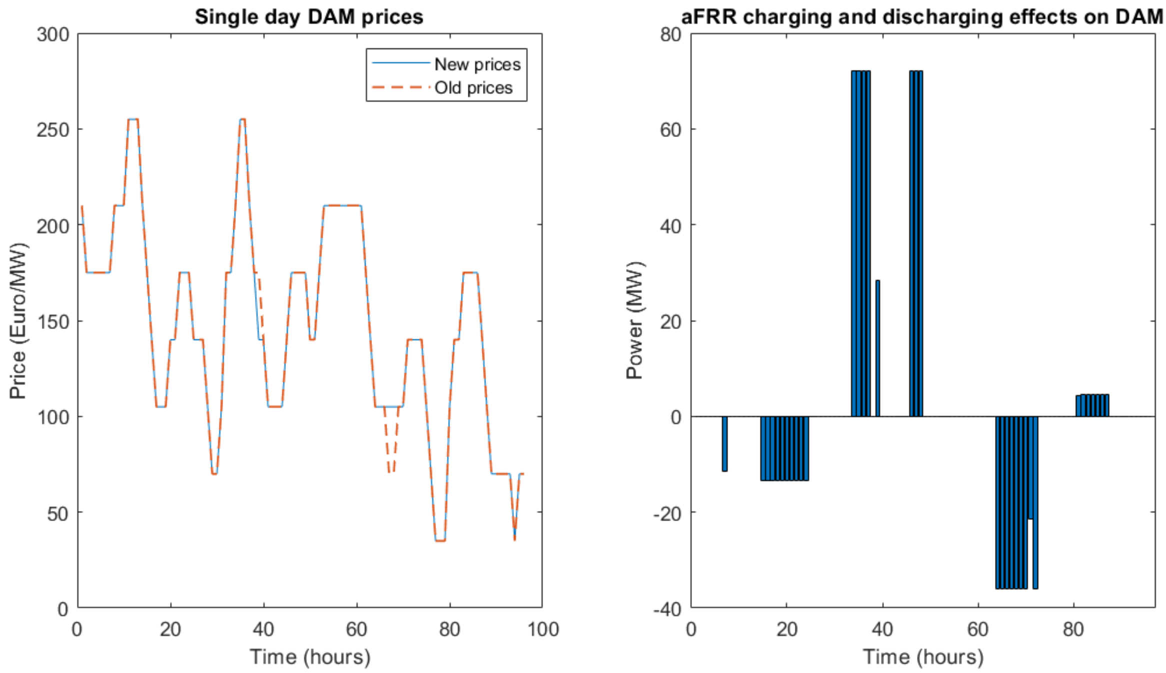

Figure 6.21: Price and behaviour of 225 MW storage system only able to participate on the aFRR market, with the influence on the DAM prices, and storage discharging and charging behaviour

The results of the implemented peak shaving algorithm are shown in Figure 6.22.

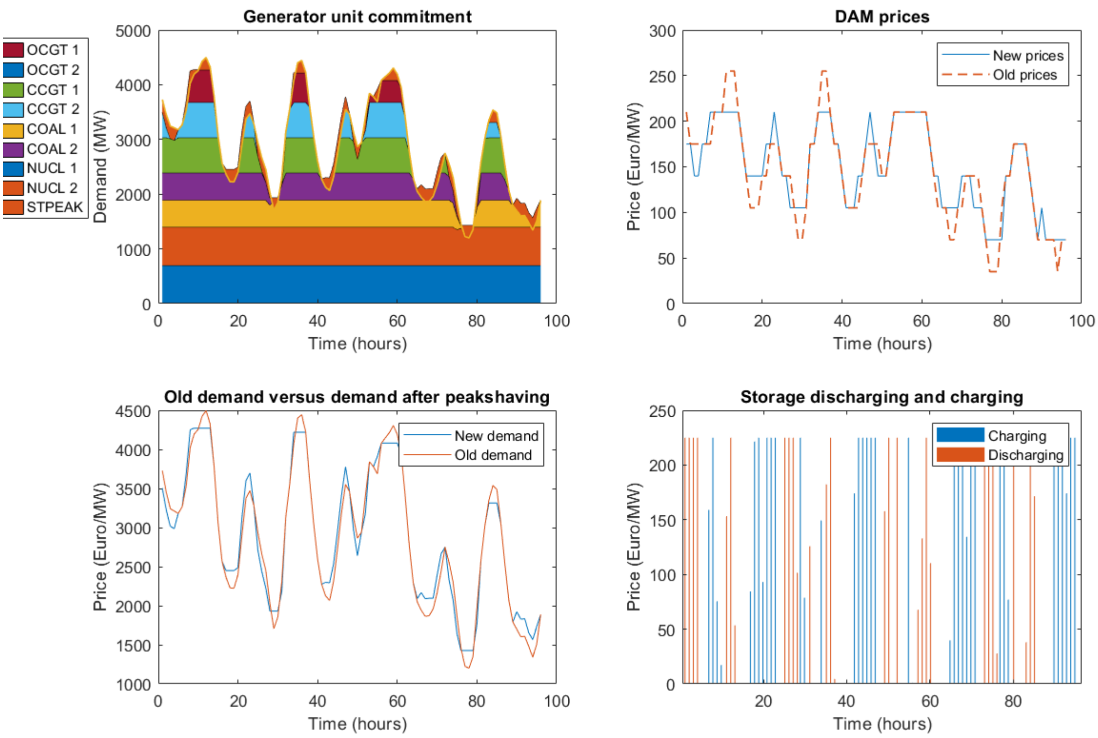

Figure 6.22: The behaviour of a 225 MW storage system that can only perform peak shaving (load levelling). Showing the generation mix, change in DAM prices, demand comparison and storage charging and discharging behaviour

The top left plot shows the unit commitment of the generators and storage participation. For clarity, the old demand curve can be seen in this plot as the yellow line. The storage system charges when activity is above this line and discharges when activity is below the yellow line. In the top right, the old and new DAM prices are seen. In the bottom left plot, the old and new demand curve is seen here the storage charging and discharging behaviour is added to the original demand. Lastly, the storage charging and discharging behaviour are plotted in the bottom right.

6.4.3. Discussion and comparison of results

Subsection 6.4.2 and 6.4.2 show the results of the storage system participating only on the aFRR market or the DAM market, respectively. The difference in overall system behaviour is quite significant, while the storage parameters are the same in both simulations. These results and discussion partly answers RQ-6.

From the DAM results, the storage system is always active within peaks and valleys and significantly influences the DAM prices. The storage system does not reduce the average electricity price, but it does reduce large price swings for both low and high prices. When looking closely at the peaks that the system is shaving (left plot), it can be seen that, in most cases, it is not an ideal peak shaver. It looks as if the behaviour of the storage systems is ”hugging” the sides of the peaks and valleys. If the self-discharge rates of the storage system were higher, then this hugging of the sides would be more to the right in the valleys, and more to the left in the peaks, such that minimal energy is lost.

The aFRR behaviour results in some minor peak shaving behaviour, but the occurrence of these peaks is random and entirely depends on the mostly random aFRR demand. Also, the influence on the DAM market is relatively small, but it can, on rare occasions, be large enough that it does change the electricity price. So this behaviour is as predicted, which is random peak shaving. However, the size of the shaven peaks is much smaller than initially expected.

So when comparing DAM and aFRR storage behaviour, it is clear that the influence of storage systems participation on the DAM is much higher than when participating on the aFRR market. Also, the DAM behaviour is peak shave-like, but with the goal of maximising profits. While aFRR is random with the objective to recover the state of charge of the storage system.

The peak shave behaviour is seen in Figure 6.22, as can be seen from the demand curves (in the bottom left plot), the valleys and the peaks are shaven off, and the demand is left with a flat top. Since the storage system is not trying to maximize profit, the overall activity, compared to the other cases, is the highest. From the top right plot, the overall DAM prices are less extreme, which is similar to the DAM behaviour. However, since the storage system does not prioritize profit maximization but maximum peak shaving, it can be seen that the price does not always become flatter and that the prices from time to time become more extreme (less flat).

6.5. Conclusions and recommendations

The overall simulation results of the complete energy model show that once storage systems start participating in the energy markets, they first join the aFRR market until this market saturates and then join the DAM. Compared to standard thermal generation, storage systems can quickly saturate the aFRR market. This is primarily due to the fast ramping capabilities of most storage systems, which allows them to bid their rated power fully. A second reason is that the capacity bid prices of storage systems compared to generators are low, which ensures that the storage systems have a high likelihood of being accepted. Due to the random nature of the aFRR energy demand, storage systems may become fully discharged or fully charged. This results in having to participate on the intraday market in order to normalize the stored energy. Another reason for aFRR accepted storage systems to participate on the intraday market is when these are only accepted for upwards regulation or downwards regulation, causing rapid energy unbalance for a small amount of ”unlucky” storage systems.

The smaller the ratio of storage capacity over power, the higher the need to participate on the intraday market. To prevent a large impact on the energy system, these smaller storage capacity systems could bid lower power in order to increase the storage over power ratio. However, this stability increase comes at a cost, which is less revenue from the balancing market.

When it comes to modelling and including the aFRR storage impact, it is possible to neglect the influence of aFRR. A reason is that in real systems, the proportion DAM over aFRR markets is much more significant. Secondly, in the simulation scenario discussed in 6.4.2, the aFRR demand had already doubled. Therefore it is safe to assume that for properly managed storage systems with enough storage capacity over power the influence on the DAM can be neglected. This influence can be more significant for storage systems with a smaller storage capacity but partly negated by properly managing power commitment.

Recommendations regarding market design

The current European market design needs some adjustments in order to increase the total storage system participation. Moreover, allow storage systems with smaller energy capacities to participate more effectively. The first change has to do with accepting capacity bids for both upwards and downwards regulation. Currently these markets are cleared separately. In future markets, it would always be recommended to accept storage bids in pairs, so if an upwards bid is accepted, then the downward bid should also be accepted.

The second change would be with respect to the capacity bidding periods. Currently, these bids are cleared once a day. In a future market, this period should be shorter since this will open up the balancing market for storage systems with lower energy capacities and faster self-discharge rates. This change allows storage systems to more frequently change their aFRR capacity bids and therefore be more active in these markets and more reliable.

Recommendations regarding improving PyPsa and including aFRR markets

Some recommendations are made regarding storage representation in PyPsa. PyPsa’s energy storage model does currently not consider the potential income streams from the balancing market. In this thesis, the influence and storage participation of the balancing markets has been thoroughly researched and simulated. Hereby can be assumed that for systems with a large enough storage over power ratio corresponding to the capacity bidding frequency. Another assumption is that the storage bids are both upwards and downwards accepted. The storage system will first participate and saturate the aFRR market before considering joining the wholesale market. This means that newly implemented storage does not impact the wholesale market until the total rated storage power (which can effectively participate in the aFRR market) is larger than the total size of the aFRR market.

To illustrate: To properly model 500MW of energy storage, the first step is subtracting a large portion of the balancing market size from the 500MW. Suppose we assume that this market has a size of 200MW. In that case, the effective storage capacity participating only on the wholesale market is equal to 500 MW - 300 MW = 200 MW, which can be simulated using the original PyPsa solver. If the market size is larger than the total capacity of the storage system, then the storage system will not participate on the wholesale market. So the DAM participation can be calculated using equation 6.15.

$$P^{dam} = \begin{cases} 0 & \text{if } P^{C,st,total} < aFRR^{C,up/down} \\ P^{C,st,total} - aFRR^{C,up/down} & \text{if } P^{C,st,total} \geq aFRR^{C,up/down} \end{cases} \tag{6.15}$$

Here $aFRR^{C,up/down}$ is the total accessible aFRR market in [MW]. If the round trip efficiency of the storage system is, for instance, 80%, then the upwards bids are 20% smaller than the downwards bids. Therefore the downwards market will saturate earlier, assuming them to be equal in size. Once one of the two markets is saturated, storage systems will participate on the wholesale market.

When using the algorithm described in subsection 6.1.2, the average revenue of small storage units performing as price takers per PTU, can be estimated by 6.16.

$$Rev = \frac{1}{4}\eta^{rte}P^{rated}(C^{up}E[\lambda^{up}] - C^{down}E[\lambda^{down}]) \tag{6.16}$$

This equation is based on the activation probability denoted by $C^{up/down}$ and the expected aFRR energy price $\lambda^{up/down}$. If the storage system has completely saturated the market, then it should not be modelled as a price taker. In this case, the revenue can be determined by the energy price set by the storage systems and expected regulation volumes: $\lambda^{up}E[Volume^{up}] - \lambda^{down}E[Volume^{down}]$.

Concerning the charging and discharging impact on the intraday market by storage systems trying to stabilise their state of charge, it is recommended that this influence be negligible for long-timescale simulations. This is possible assuming storage capacity is appropriately large, and control algorithms are well implemented.

7 Conclusion

In this thesis, a comprehensive overview was given of most of the energy storage technologies and applications. This led to useful generalisations regarding both the application and technology of energy storage systems. So can most storage systems technologies be modeled using a limited set of parameters, for example SOC and efficiency. Also the storage applications and services can be categorized into three different groups, peak-shaving, power quality and arbitrage. Also, the European energy markets, like the aFRR market and the DAM, were discussed, showing the different design possibilities, and providing some tools to help model these markets.

In chapter 5, multiple modelling methods of storage systems providing grid services have been analysed and explored. This has led to valuable insights regarding the viability of different modelling methods and specific difficulties, challenges and limitations. The modelling has been done by exploring two separate approaches: a top-down (LLP) approach and a bottom-up (ULP) approach. Based on these insights, a complete energy system model could be made, and this was done by combining the more prominent specific purpose models into one model and adjusting these. The complete energy system simulates thermal generators participating in multiple energy markets and the optimal participation of storage systems within those markets. The simulation results show that the impact (the charging and discharging need on the intraday market) of storage systems participating in the aFRR market is small. Thereby assuming that storage systems have proper control algorithms and sufficient storage capacity such that it does not deplete within a single time interval. The results show that storage systems behaving optimally will participate in the balancing markets, like the aFRR market, until these markets saturate. Only then these storage systems will start participating in the wholesale markets like the DAM. The simulation results of the complete model have led to multiple recommendations regarding general energy market design discussed in 6.5, and the proper representation of storage systems within existing models discussed in 6.5, mainly focusing on the proper representation aFRR.

The research questions [RQ-1] until [RQ-6] where answered throughout this thesis. Firstly to answer [RQ-1], it was shown by the results of chapter 6 6.2, that profit-maximizing storage systems would first join the balancing markets before they start participating in the wholesale markets, thereby not trading in the day-ahead market until the aFRR market is saturated.

Section 3.1, looked at the applications of storage systems, where the influence of all storage applications could be modelled as three more straightforward applications: Arbitrage, peak-shaving and power quality. Furthermore, chapter 6 showed that the charging and discharging impact on the wholesale market of the power quality-related services (FCR and aFRR) could be neglected, which together answered [RQ-2].

[RQ-3] was answered in 5.2.3. In this subsection, the model showed profit maximizing storage systems only performing arbitrage (ULP) behave the same as when this storage system is activated using a model that minimizes overall system costs (LLP).

[RQ-4] was answered in chapter 5, where modelling methods and strategies were explored. These mainly were optimization-based modelling but also looked at different approaches to model the same storage applications, like the ULP and LLP approaches.

[RQ-5] is answered in 6.5, where concrete recommendations are given on representing these storage applications into existing models such as PyPsa, which was to subtract the available balancing market size from the total storage capacity to find the correct influence on the wholesale markets.

Lastly, [RQ-6] is answered in 6.4, where was shown that the impact of storage systems providing aFRR could be neglected. At the same time, the influence of arbitrage and peak-shaving should be considered. However, here is also stated that the representation of peak-shaving in this model should be further improved.

7.1. Future work

The representation of regulation within optimisation-based models proved challenging due to the random nature of the aFRR demand. Ideally, optimal storage participation among different European energy markets should be possible by implementing stochastic or robust optimisation principles. However, the theory and options regarding stochastic optimisation methods are quite excessive. Therefore, given this thesis's time span and objective, further exploring these concepts could not be adequately done.

The current implementation of the large-scale distributed storage systems providing peak shaving is very roughly approximated. The more accurate behaviour should be further investigated, as peak shaving storage systems will likely to increase in the future. As a result, the focus should be on the combined effects of differently implemented peak shaving algorithms, with a better representation of the local grid topology, the local boundaries, and the local power flow while taking into account the different peak shaving levels.

The downwards aFRR representation is in the current energy system model not complete since, in practical systems, there is a chance that the downwards aFRR prices are negative. In future versions which specifically focus on aFRR modelling, it would be an improvement if this was represented.

7.2. Reflection

Many of the goals set in the earlier stages of the thesis were accomplished. However, the time required to adequately model aFRR and its specific market mechanisms were underestimated. This resulted in FCR and Peak shaving being underrepresented in the current implementation. The complete market design and energy storage participation in those markets was a subject which was previously thought to be specific, in reality, however, each individual market, storage model and application is deserving of its own much more detailed thesis. I believe that the goals regarding the representation of aFRR, have led to better tools to represent aFRR and that this forms a foundation for new research directions regarding better ways to represent storage.

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