

# The Hybrid Power Plant

Optimal design and operation of battery energy storage as an addition to onshore wind farms in the Netherlands



A master thesis by Lennard Sijtsma

  
**TU Delft**

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# Optimal design and operation of battery energy storage as an addition to onshore wind farms in the Netherlands

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L.C. (Lennard) Sijtsma

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<sup>1</sup> Please note that when I started my master thesis project, the company was still called Ecofys (a Navigant company). It has since undergone a name change to Navigant, but both company logo's are represented on the cover.

## Executive summary

In the pursuit of a power portfolio less dependent on fossil fuel fired power plants, renewable energy sources become more and more ubiquitous. In the Netherlands, wind power has the highest potential for future development compared to alternatives such as solar PV and biomass. The intermittent nature of the wind power resource calls for novel approaches to supply and demand management, as well as power quality assurance. Energy storage technologies allow for the separation between power generation and power supply to the grid. The energy and power densities, efficiency and response times of secondary batteries make them highly suitable for utility scale application to wind farms. However, a knowledge gap exists on exact configurations of battery energy storage systems for wind farms within the existing power markets. This study proposes a hybrid power plant approach, combining an onshore wind farm with a battery energy storage system. The research questions of this project are:

**Q.** *How can battery energy storage be optimally designed and operated for onshore wind farms in the Netherlands?*

**q1.** *What criteria determine whether the hybrid power plant is optimally designed?*

**q2.** *Which wind power and battery characteristics influence the optimization criteria established in q1?*

**q3.** *Which energy markets are relevant to the hybrid power plant?*

**q4.** *What is the optimal configuration of the hybrid power plant?*

**q5.** *How can the hybrid power plant be optimally operated daily?*

Literature research identifies balance between power obligation and production as a main design criterium, along with the profitability of a configuration and operational strategy. A technical analysis establishes power fluctuation on multiple time scales as relevant wind power characteristics, and maximum depth of discharge, discharge rates and efficiency as important battery parameters. A detailed analysis of the Dutch power market structure identifies three accessible markets for trade: the Day Ahead Market, the primary reserve (FCR) and the secondary reserve (aFRR). For modelling and optimization purposes, FCR is not considered due to excessive uncertainties regarding bid acceptance and bid activation.

The design phase of the study is charged with finding the optimal battery capacity for a given wind farm production, while assuring the obligation to the Day Ahead Market is met. A linear optimization model is developed with the objective to maximize the obtained revenue. It is shown that the optimal battery capacity scales with the power capacity of the wind farm. For a 60 MW wind farm, the optimal battery capacity lies within the range of 60 – 80 MWh.

An operational model is designed based on the model of the plant established in the design phase, elaborated with a Model Predictive Control approach. Based on wind power generation forecasts, the algorithm is able to adjust the charge/discharge and imbalance settlement strategy continuously based on expected market price series. However, the low level of accuracy of the applied market price approximations lead to unprofitable results in all simulated cases. Market price approximations with

increased accuracy, as well as reduction of battery installation costs may lead to profitable operation of a hybrid power plant.

Recommendations for future work include more accurate financial modelling, the addition of the FCR market in the operation of the plant and novel methods for market price approximations. Accurate financial modelling requires consideration of interest, inflation and net present value of the system. The FCR market is identified as an accessible source of revenue for the hybrid power plant, and accurate market approximations could increase the revenue potential of the hybrid power plant. Finally, as indicated by the operational tool, market price approximations with high accuracy are required to profitably operate the hybrid power plant.

In addition to this summary, each chapter closes with a set of comprehensible statements summarizing the chapter under the title 'Key Takeaways'.

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## Abbreviations

AC	Alternating current
aFRR	Automatic frequency restoration reserve
APX	Amsterdam Power Exchange
CAPEX	Capital expenditures
CET	Central European Time
DAM	Day Ahead Market
DOD	Depth of discharge
DSO	Distribution system operator
ENTSO-E	European Network of Transmission System Operators for Electricity
EU	European Union
EUR	Euro
EV	Electric vehicle
FCR	Frequency containment reserve
FRR	Frequency restoration reserve
GW	Gigawatt
Hz	Hertz
kV	Kilovolt
kW	Kilowatt
kWh	Kilowatt-hour
LCO	Lithium cobalt oxide
LCOS	Levelized cost of storage
LFP	Lithium iron phosphate
LMO	Lithium manganese oxide
LTO	Lithium titanate
mFRR	Manual frequency restoration reserve
MPC	Model Predictive Control
MW	Megawatt
MWh	Megawatt-hour
NCA	Lithium nickel cobalt aluminum oxide
NMC	Lithium nickel manganese cobalt oxide
OPEX	Operational expenditures
PRP	Program responsible party
PV	Photovoltaic

RMSE	Root mean square error
ROI	Return on Investment
SOC	State of charge
TSO	Transmission system operator
TWh	Terawatt-hour
UNFCCC	United Nations Framework Convention on Climate Change
USD	United States Dollar
V	Volt
W	Watt
WPS	Wind Prediction Services

## Symbols

<b><math>BC</math></b>	Battery installation cost
<b><math>BL_t</math></b>	Battery level at PTU $t \in \{1, 2, \dots, T\}$
<b><math>BL_{t,t'}</math></b>	Battery level at PTU $t' \in \{1, 2, \dots, h\}$ within run $t \in \{1, 2, \dots, T\}$
<b><math>BS</math></b>	Battery size (volume capacity)
<b><math>CAPEX</math></b>	Capital expenditures
<b><math>CF_t</math></b>	Capacity fade due to cycling at PTU $t \in \{1, 2, \dots, T\}$
<b><math>CF_{t,t'}</math></b>	Capacity fade due to cycling at PTU $t' \in \{1, 2, \dots, h\}$ within run $t \in \{1, 2, \dots, T\}$
<b><math>CL</math></b>	Battery cycling life in number of full charge/discharge cycles
<b><math>DOD</math></b>	Maximum allowable depth of discharge
<b><math>E_t^{act}</math></b>	True production of the wind farm at PTU $t \in \{1, 2, \dots, T\}$
<b><math>E_{t,t'}^{act}</math></b>	True (or expected) production at PTU $t' \in \{1, 2, \dots, h\}$ within run $t \in \{1, 2, \dots, T\}$
<b><math>E_t^C</math></b>	Positive charge volume at PTU $t \in \{1, 2, \dots, T\}$
<b><math>E_{t,t'}^C</math></b>	Positive charge volume at PTU $t' \in \{1, 2, \dots, h\}$ within run $t \in \{1, 2, \dots, T\}$
<b><math>E_t^{DAM}</math></b>	DAM obligation based on bid at PTU $t \in \{1, 2, \dots, T\}$
<b><math>E_{t,t'}^{DAM}</math></b>	DAM obligation based on bid at PTU $t' \in \{1, 2, \dots, h\}$ within run $t \in \{1, 2, \dots, T\}$
<b><math>E_t^D</math></b>	Positive discharge volume at PTU $t \in \{1, 2, \dots, T\}$
<b><math>E_{t,t'}^D</math></b>	Positive discharge volume at PTU $t' \in \{1, 2, \dots, h\}$ within run $t \in \{1, 2, \dots, T\}$
<b><math>E_t^{export}</math></b>	Positive volume sold to imbalance market at PTU $t \in \{1, 2, \dots, T\}$
<b><math>E_{t,t'}^{export}</math></b>	Positive volume sold to imbalance market at PTU $t' \in \{1, 2, \dots, h\}$ within run $t \in \{1, 2, \dots, T\}$

$E_{t,t'}^{imbalance}$	Net volume settled on the imbalance market at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$E_t^{import}$	Positive volume purchased from imbalance market at PTU $t \in \{1,2, ... T\}$
$E_{t,t'}^{import}$	Positive volume purchased from imbalance market at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$EMP_{t,t'}^{DAM}$	Expected Day Ahead Market price at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$EMP_{t,t'}^{imbalance}$	Expected export price at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$\eta^C$	Charge efficiency
$\eta^D$	Discharge efficiency
$\eta^R$	Round-trip efficiency
$h_1$	Optimization horizon DAM module expressed in number of PTU's
$h_2$	Optimization horizon intraday module expressed in number of PTU's
$H_N$	Negative host material in a lithium-ion battery
$H_P$	Positive host material in a lithium-ion battery
$LT$	Battery lifetime expressed in number of PTU's
$MP_t^{DAM}$	Day Ahead Market price at PTU $t \in \{1,2, ... T\}$
$MP_{t,t'}^{DAM}$	True Day Ahead Market price at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$MP_t^{export}$	Export price at PTU $t \in \{1,2, ... T\}$
$MP_{t,t'}^{imbalance}$	True imbalance price at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$MP_t^{import}$	Import price at PTU $t \in \{1,2, ... T\}$
$NC$	Net connection capacity expressed in maximum allowable PTU volume
$OPEX$	Operational expenditures
$R_{OC}$	Ratio of OPEX to CAPEX
$T$	Number of PTU's in simulation
$t$	Time expressed in number of PTU's passed (current run identifier MPC)
$t'$	Specific PTU within a run
$TC_t$	Total volume previously charged at PTU $t \in \{1,2, ... T\}$
$TC_{t,t'}$	Total volume previously charged at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$TF$	Total fraction of battery capacity faded at end-of-life

## Chapter 1: Introduction

## Context

The level of global warming due to human activities reached 1°C in 2017 relative to pre-industrial temperatures and is likely to increase at 0.2°C per decade. As a cause of the global increased average temperature, extreme weather events are more likely to occur, ocean and sea water levels are expected to rise, and risks to the global food supply emerge (Allen, et al., 2018). The socioeconomic effects are enormous, and within this context, a multilateral agreement dealing with greenhouse-gas mitigation, societal and industrial adaptation and finance was drafted during the 21<sup>st</sup> Conference of the Parties of the UNFCCC. The Paris Climate Agreement has been signed by 195 countries in 2015 and ratified by 187 countries as of January 2019. Its central aim is *'to strengthen the global response to the threat of climate change by keeping a global temperature rise this century well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5°C'* (UNFCCC, 2019). One of the most significant implications is to decrease the global emissions of greenhouse gases by 49% by 2030. In accordance with the Paris Climate Agreement and the corresponding Energy Agreement for the Netherlands, the Dutch government has since published a Climate Agreement draft ('Ontwerp van het Klimaatakkoord') which deals with the 49% CO<sub>2</sub> reduction aim and states the intent for a CO<sub>2</sub> free power generation system by 2050. Direct implications of the Climate Agreement are to upscale the power generation from renewable energy sources, both onshore as well as offshore, to replace greenhouse-gas intensive fossil fuel fired power plants (Sociaal-Economische Raad, 2019).

Driven by these multilateral agreements between climate agencies, governments and industry, the global power generation portfolio is increasingly represented by renewable energy sources such as solar PV and wind power. In 2010, solar PV and wind power generation projects accounted for less than 25% of the annual power capacity addition worldwide. Over the course of just six years, the global annual addition of solar PV and wind power generation has increased to match the annual addition of fossil fuel-based sources (IEA, 2017), as indicated in Figure 1. Power prices of electricity from solar PV and wind power generation are becoming more and more competitive, a trend driven by technological advancement, competitive procurement and a growing base of experienced project developers (IRENA, 2018). While the reduction of greenhouse gas emissions during the generation of power can be reduced significantly by these measures, the renewable energy sources pose new challenges in grid

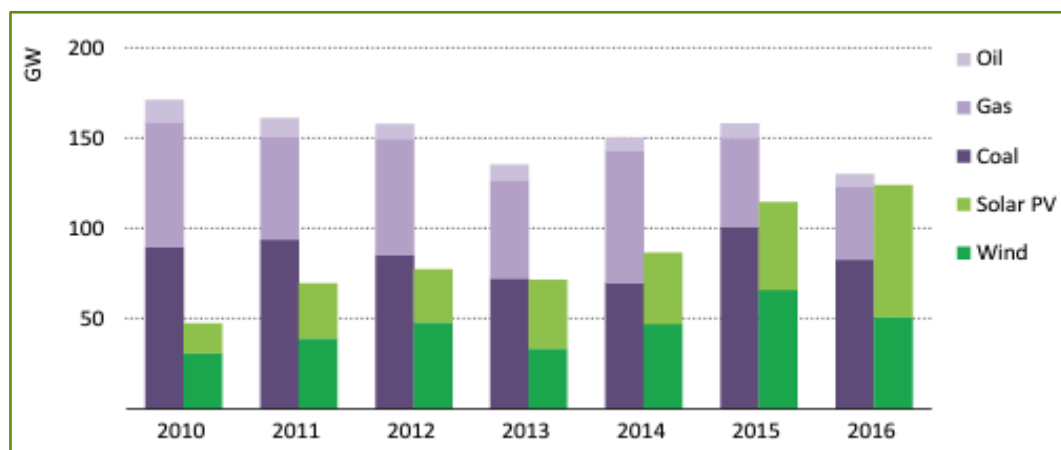


Figure 1: Annual capacity additions of solar PV and wind power generation have been closing the gap with fossil fuels (IEA, 2017)

construction and management. The fossil-fuel power plants make for a controllable and therefore reliable power generation. These power plants rely on storable fuels, whereas solar PV and wind power generation rely on current weather conditions. The net is designed according to the reliable fossil-fuel power plants. The introduction of intermittent sources, such as weather dependent solar PV and wind power generation may not pose any problems on a small level of grid penetration, but as these sources become increasingly ubiquitous and since the global electricity demand is expected to increase significantly in the next decades, grid stability issues will arise if no precautionary measures are taken. The level of grid penetration at which these issues arise depends on the grid flexibility and is on average approximately 30% (IEA, 2011).

Simultaneously, it is expected that society will be more and more dependent on electricity for day to day life. Electricity demand will rise due to multiple factors, such as the accelerating adoption of electric vehicles (EV's) and the introduction of heat pump systems as a valuable alternative for domestic heating. Additionally, the potential of electrification in industry is high, driven by power to heat and electric steam generation (Schüwer, 2018). Developing countries will see rapid integration of large domestic electrical appliances as these technologies become more available. In advanced economies, the growth in electricity demand is expected to be less than 1% on an annual basis, whereas developing economies will see an annual 3% growth. To put this in perspective, in ten years from now, the global electricity demand is expected to be more than 40% larger than today (IEA, 2017). The trend of increasing dependence on electricity runs parallel with the rapid development of renewable energy sources and its growing presence in the power supply.

The main characteristic of these specific renewable energy sources is their weather and climate dependency; the power production of these sources is dominated by intermittency. This intermittency can cause problems on multiple time-scales, ranging from seasonal fluctuations all the way down to 20 milliseconds related to a 50-Hz AC net frequency. To assure an adequate national power portfolio, interconnection between countries is required to settle local surpluses or deficits (DOE, 2018). Furthermore, the development of smart grids is an important measure in an electrifying society with increasing levels of intermittent renewable energy penetration. These smart grids rely on two-way communication between generating and consuming parties, allowing for automated actions based on the exchanged information (DOE, 2018). For wind power generation, three timescales can be identified on which power fluctuations occur. The largest variation in terms of wind capacity is the seasonal effect. During the summer months, wind power potential is significantly lower than during the winter months (EIA, 2015; Sinden, 2007). Potential measures to account for seasonal fluctuation in generating capacity include long term energy storage in the form of pumped hydro or power-to-fuels (including power-to-hydrogen). On a daily basis, the wind power potential at night is significantly lower than during daytime (Sinden, 2007), and measures to account for this include demand response (on the consumption side of the electricity chain) and short-term energy storage. Finally, especially in a grid with high dependence on wind power, fluctuations with a timescale of a minute can become of high importance (Sørensen, 2007). This smallest timescale can cause power and frequency fluctuations in

the power supply, and these are critical issues related to wind power generation (Yao, 2012). All three timescales of fluctuations pose their own challenges in the security of supply of power.

To secure a reliable production portfolio on a national level, measures must be in place to match supply and demand of power on all timescales, and at all four intermediate steps in the electricity supply chain: generation, transmission, distribution and consumption. At the source, power plants must be able to quickly deal with fluctuating generation to fulfill their market obligation. The transmission network must monitor and maintain the real time balance between uptake from the grid and the volatile injection to the grid. Electrification of transport and industrial and residential heating, along with increased shares of intermittent renewable energy sources requires intelligent allocation of power by distribution system operators (DSO). At the level of consumption, consumers must be enabled to monitor and manage their electricity and incentivized to contribute to ensure a balanced grid.

While offshore wind power development in the Netherlands is expected to surge, onshore wind power still serves a significant role in the Dutch power system. The potential role of solar PV in the Netherlands cannot be marginalized, however, at this point, the focus of future development is in wind power. Considering the vital role onshore wind energy will play in the coming decade, its intermittent nature, and the opportunities posed by battery energy storage, this study will focus on optimal integration of these technologies to mitigate the short-term intermittency of wind energy. Short term intermittency is associated with power fluctuations on the smallest timescale (milliseconds) to a daily timescale. The issues associated with intermittency on the shortest timescale are frequency and voltage deviations from the setpoint. These deviations can lead to power surges or shortages capable of causing damage to the transmission system. On a timescale of several hours up until a full day, one of the main issues is the mismatch of supply and demand on a grid level. Measures such as interconnection and control reserves are in place to counteract these challenges, but for an increasing penetration of intermittent renewable energy sources, additional options must be explored. A hybrid power plant is hereby proposed, referring to the combination of an onshore wind farm and a battery system to form a new type of power plant with unique characteristics. The scale of offshore wind energy (several hundreds of megawatts, as opposed to a maximum of 100 MW for onshore wind farms) requires energy storage methods of larger power and energy capacities. In theory, battery energy storage is still a viable option, but other options such as power-to-fuel, power-to-gas (including hydrogen) and pumped hydro energy storage are more potent for offshore wind energy. The ensuing literature review is performed to further investigate the role of wind energy in the current and future energy scenario's; to analyze similar projects and applications of battery energy storage and to determine the role of power markets when trading power generated by the hybrid power plant.

## Literature review

The increase of wind power generation within the Dutch electricity supply is quantified in the Nationale Energieverkenning 2017 (ECN, 2017), and is illustrated in Figure 2. The role of wind power was nearly

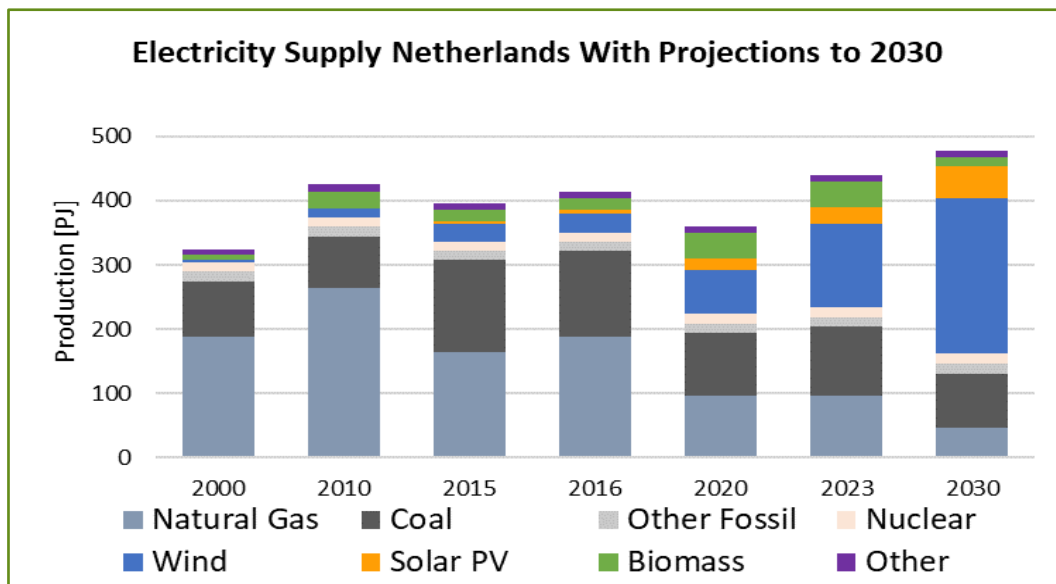


Figure 2: The state of the Dutch electricity supply up to 2016 is based on installed capacity of all available sources, whereas the projections to 2030 are based on pledged projects and developing policies regarding the energy landscape (ECN, 2017)

negligible less than 20 years ago, accounting for only 1% of the electricity production. At present, this share is less than 10%, but it is expected that within five years, the share will grow to 29%, and to 51% by 2030. Currently, the ratio of onshore to offshore wind power capacity in the Netherlands is about 5:1 (ECN, 2017; Bosch & van Rijn, 2018), but in a decade time, offshore wind power capacity will have outgrown the onshore capacity. The mid- to large size onshore windfarms (more than 10 turbines) have an average power capacity of 31 MW. The largest onshore windfarm has a power capacity of 192 MW, while the second largest windfarm has a capacity of 126 MW. Offshore wind farms do not face the same geographical and societal constraints, and the potential for offshore expansion is indicated by the fact that currently the smallest offshore wind farm in the Netherlands has a generating capacity of 108 MW, and the largest 300 MW (Bosch & van Rijn, 2018). Another visible trend in Figure 2 is the overall increased production of electricity from 2020 to 2030, which can be explained by the shift away from natural gas reliant commercial heating and major increases in the sale of EV's (Navigant Research, 2017). Since the role of renewable energy in the electricity supply is expected to grow, the role of fossil fuel-based sources will be reduced. The reduction in greenhouse gas emissions make this a significant and positive development. However, the current power grid is built on the reliable properties of these sources. Compared to renewable energy sources, gas or coal fired power plants are able to scale the production up or down relatively easily. The intermittent nature of renewable energy sources such as wind power generation and solar PV can cause instability to the power system when unexpected dips or spikes in the generation occur. Integration of renewable distributed generation has a significant effect on the voltage profile and network losses (Mahmud & Zahedi, 2016; Yang, 2018).

Energy storage allows for separation between the generation of power and the actual supply to the grid. This is done by transferring electrical energy by conversion into another form of energy, which can be either (electro-) chemical, electrical, mechanical or thermal energy. A possible classification of individual storage methods is presented in Figure 3. To match the seasonal supply and demand profiles, large scale energy storage methods such as pumped hydro, hydrogen generation by electrolysis or

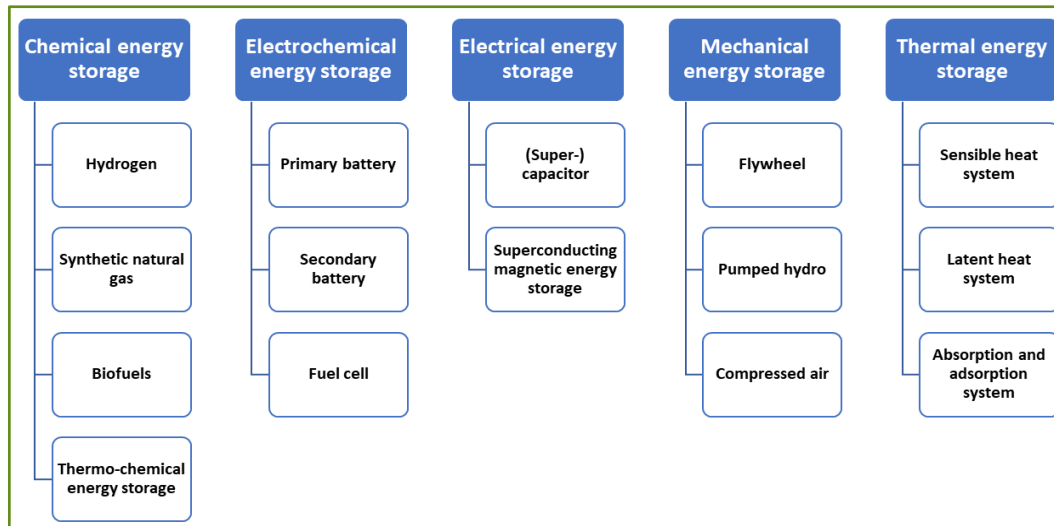


Figure 3: Classification of energy storage systems by technology (Guneay & Tepe, 2017)

compressed air energy storage are required. These technologies allow for storage of large volumes of energy for significant durations. The daily wind power generation cycle requires lower volumetric storage capacity, but quicker response times. Suitable technologies for this timescale include battery energy storage systems, but the previously mentioned technologies may be able to operate on this timescale as well, given the response and ramp times are sufficiently small. On the shortest timescale regarding power and frequency fluctuations, the high capacity technologies do not possess adequate response times, but technologies such as flywheel energy storage become a viable option alongside battery energy storage (Reihani, Motalleb, Ghorbani, & Saad Saoud, 2016; Díaz-González, Sumper, Gomis-Bellmunt, & Villafáfila-Robles, 2012).

A case study is performed by Balischewski et al. in which battery energy storage use cases are defined which allow for reduction of operating costs for wind farms (Balischewski, et al., 2017) in Germany. A battery system design is proposed in this study with the purpose of fulfilling peak power requirements of the wind farm operations, instead of importing this reactive power from the net. The study concludes that such a system configuration can return profit when optimally scaled. The authors also claim that the diverse applicability of batteries make that additional use cases can be defined and implemented to support the single use case that is investigated. Configuration optimization is applied in order to maximize cost reduction, however, real-time operational strategies are not discussed in this paper.

Jiang et al. pose that the main challenge behind increasing wind power penetration is the intermittent power output (Jiang, Gong, & Wang, 2013). A dual-layer control strategy is proposed to mitigate the wind farm power output fluctuations using a battery energy storage system. The first layer deals with wind power fluctuation mitigation by restoring a surplus or deficit in power production with regards to the expected power production through respectively charging or discharging the battery system. The second layer deals with power allocation to the individual storage units of the battery system. The main objective of this dual-layer control strategy is to account for short term fluctuations and unexpected dips or spikes in power production.

Li et al. have developed a power smoothing control scheme for photovoltaic and wind power generation fluctuations relying on battery energy storage (Li, Hui, & Lai, 2013). The study considers an existing hybrid power plant, consisting of a 100 MW wind farm, a 40 MW solar PV farm and a 14 MW/63 MWh lithium-ion battery energy storage system in the Zhangbei region of China. The authors state that control methods to achieve a smooth power output is required to realize a robust injection to the electricity grid. The main concern of this study is the tradeoff between smoothness of the power generation profile and battery effort (the intensity of battery use). A smooth power generation profile is predictable, and therefore favorable. The authors claim that previous studies have disregarded this level of smoothness. This study therefore introduces targets for power control which incorporate the tradeoff between smoothness and battery effort. Similar to the study performed by Jiang et al., the proposed solution consists of power fluctuation mitigation as well as power allocation to individual battery units.

The main message of these studies is that battery energy storage, when properly applied to a wind power generation system, can provide to be valuable to the plant operator through supply and demand balancing and ancillary services. One of the key challenges, however, is the profitability of such a configuration, as discussed in the Balischewski paper. While the services provided to the power output of the intermittent energy sources are valuable to the plant and grid operators in terms of reliability, revenue streams have not been identified as of yet. This study aims to provide a techno-economical assessment for battery energy storage systems, providing balancing and ancillary services, for onshore wind farms in the Netherlands. The separation between generation and supply to the grid allows for the potential of value increase of electricity. Power generated at a time of low market prices, caused by a surplus of generation capacity on a grid level, may be stored to be discharged at a time of high market prices and a deficit in generation capacity.

A great illustration of this phenomenon is presented in the work of Zhai et al. (Zhai, Meng, Dong, & Ma, 2017). The main purpose of this study is to develop a method to provide frequency regulation services using second-life lithium-ion batteries from EV's within the Australian market framework. In contrast to the previous studies, this study regards a stand-alone battery energy storage system. The proposed method allows the market mechanism to determine when, in which markets and by what energy source the lithium-ion battery is operated. The study shows significant profit potential and concludes that simultaneous trading on both the spot market as well as the frequency control reserves can be twice as profitable as opposed to single-market trading. While the study does not consider wind power generation, the value streams of the stand-alone system in the Australian market framework identify the opportunities for other frameworks as well.

The work of Dicorato et al. proposes a combined wind-storage system, with the purpose to smooth the unpredictable variations in wind generation to follow the scheduled plan (Dicorato, Forte, Pisani, & Trovato, 2012). The study considers sodium-sulfur batteries to have the most favorable characteristics for the purpose of power smoothing. One of the drivers is that variations in power plant load require transmission system operators to purchase resources on the Auxiliary Services Market. The authors propose a control algorithm to determine the energy delivery of the combined wind-storage system as to circumvent the settlement of variations on the appropriate market. By tailoring the delivery plan to

the appropriate market signals, it is shown that the proposed system and control scheme can be profitable.

This is supported by a study performed by DNV GL in the Netherlands. They report that the hybrid system configuration of a wind farm and a battery energy storage system can generate revenue by trading electricity imbalance of the plant (Energeia, 2017). The main conclusion is that combining energy storage with wind turbines can lead to positive results regarding profitability, under specific circumstances. One of the requirements is optimal sizing of the battery system; a large capacity system will result in relatively lower levelized cost of storage, but an oversized system can lead to additional net connection costs if the cumulative power capacity of the system exceeds the net connection capacity. Another requirement is that the storage system is dispatched for multiple purposes, such as prioritizing self-consumption which can eventually lead to lower net connection costs.

The importance of energy storage in a power system increasingly reliant on intermittent sources such as wind power generation and solar PV is indicated by these studies. The main drivers are to reduce the short-term variation in power generation and to increase the accuracy of a submitted program or market obligation. Apart from the beneficiary services that battery energy storage can provide, either as an addition to a wind farm or as a stand-alone system in a power grid, it has been shown that investments can be profitable if planning and dispatch of the storage system is optimized. Imbalance occurs when the planned or pledged production profile of a power plant does not match the true production at any given time. While it is shown that trading in imbalance can be aided with battery energy storage and make for a profitable investment in the Netherlands in such a system, a knowledge gap exists regarding exact configurations of such a system and the role it can serve in the Dutch power markets. This study aims to fill the identified knowledge gap, as summarized by the following drivers. First, to assess the role of battery energy storage for the generation of wind power in the Netherlands. Second, to analyze the Dutch electricity system to identify sources of revenue and trading strategies. Finally, to develop an operational tool that determines the charging schedule of the battery energy storage system.

## Research questions and scope

The research drivers that have been established lead to the formulation of research questions. The main research question is:

**Q.** *How can battery energy storage be optimally designed and operated for onshore wind farms in the Netherlands?*

A combined system configuration of a wind farm with battery energy storage will be referred to as a hybrid power plant. Optimal application of battery energy storage within such a hybrid power plant is a subjective qualification, and a clear definition needs to be established. The further sub questions (denoted by **q.** for future reference) deal with the characteristics of the individual systems and markets, design and sizing of the overall system, and finally the development of an operational tool.

**q1.** *What criteria determine whether the hybrid power plant is optimally designed?*

**q2.** Which wind power and battery characteristics influence the optimization criteria established in **q1**?

**q3.** Which energy markets are relevant to the hybrid power plant?

**q4.** What is the optimal configuration of the hybrid power plant?

**q5.** How can the hybrid power plant be optimally operated daily?

In formulating the research questions, some restrictions to the scope of the study have already become apparent. The study will focus on **battery energy storage** to aid the **daily and continuous** production of **onshore wind power generation in the Netherlands**, limited by the time resolution of the available data. Since onshore wind farms are geographically constricted in terms of the number of turbines that can be installed, this study considers wind farms with a maximum generating capacity of **100 MW** (based on the data from Bosch & van Rijn and ECN).

## Approach

This study deals both with the design and configuration of a hybrid power plant operating in the Dutch power system, as well as with the operation of the proposed plant. These two phases (design and operation), though inarguably interconnected, have a distinct point of view. Whereas in the design phase the wind power generation profile is a given and the sizing of the battery must be optimized, both are considered as given for the development of the operational tool. During the design phase, 'perfect foresight' is applied regarding power generation and market prices, while the operational tool is specifically designed to function under realistic assumptions regarding the relevant markets, since power generation and market prices can not be predicted with full accuracy.

In order to find the answer to the sub questions, and with it the main research question, the steps in Figure 4 are proposed. The literature review has already led to the identification of optimization goals of a hybrid power plant: the reduction of imbalance between planned and true production of a wind farm, and generation of revenue to fund the investment. The hybrid power plant consists of a wind farm and a battery system, both with distinct characteristics that are determined by means of a technical analysis using literature, textbooks and web sources. These characteristics must be captured in parameters, to allow for proper modelling of the system. On the other side of the spectrum, a market

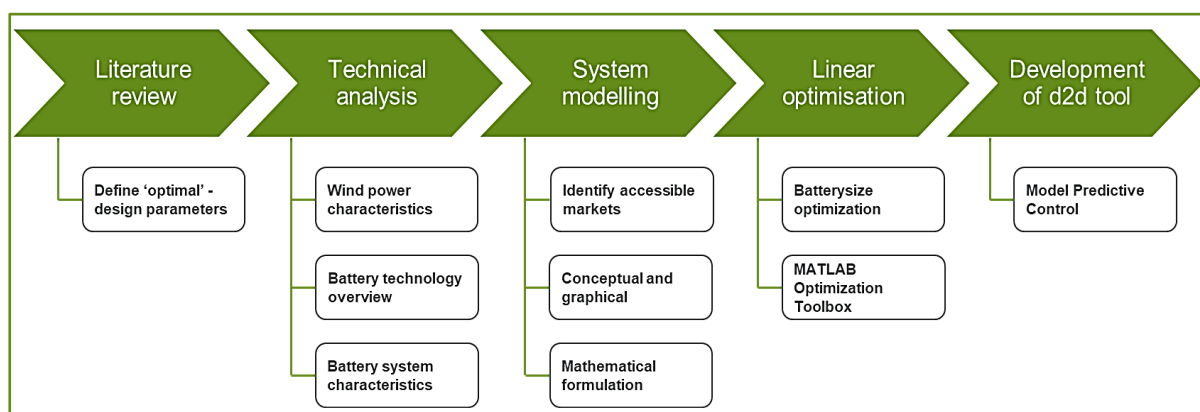


Figure 4: Graphical representation of the research steps, the five steps closely correlate to the five sub questions of the study

analysis must be performed to identify accessible markets for a hybrid power plant. A conceptual model is proposed, graphically represented and translated into a linear set of equations. The mathematical model serves as the basis of the optimization of the system configuration, and execution of the algorithm returns results on balancing capability and profitability.

## Report framework

This report aims to provide a comprehensive overview of the performed work. Chapter 2 will describe the current state of wind power generation in the Netherlands, along with a brief technical review regarding the characteristics of a wind farm. In chapter 3, the working principle and state of the art of batteries is analyzed. Based on key indicators, a specific battery technology is chosen, and its performance is caught in a set of parameters. The Dutch electricity market mechanisms are described in chapter 4, and accessible markets with potential for revenue streams are identified. The conceptual model, along with its graphical representation is presented in chapter 5. This conceptual model is expanded with assumptions and the constraints of the individual systems in the configuration, and all this is translated into a mathematical formulation. The model serves as the basis of the hybrid power plant configuration optimization, from which the results are discussed in chapter 5 as well. In chapter 6, an operational tool is proposed and presented along with the simulation results. Finally, chapter 7 serves to conclude the study, and to give recommendations for future work on this subject. Figure 5 gives a schematic overview of all the chapters and their relation to one another.

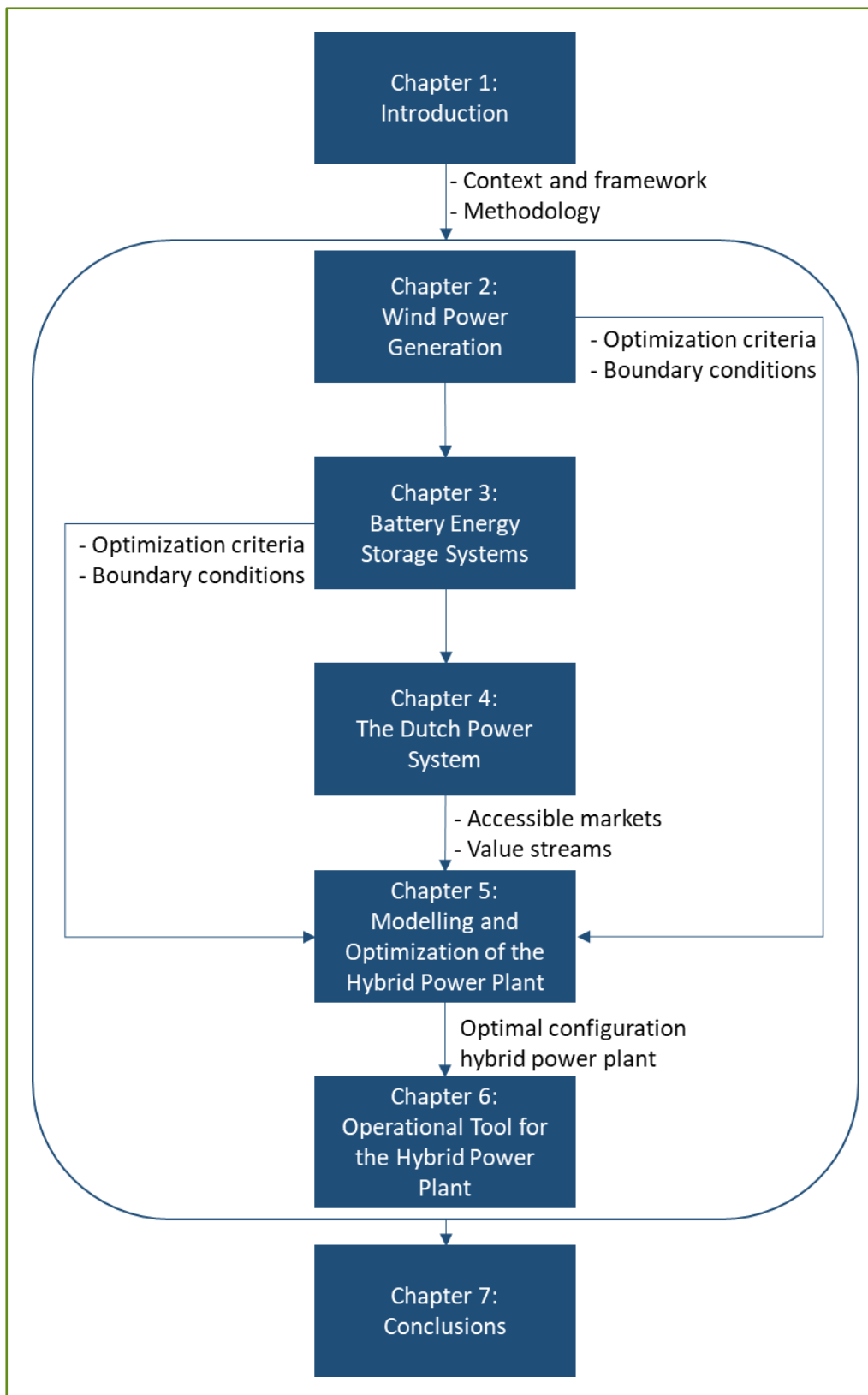


Figure 5: Schematic overview of the consecutive chapters and their relation to one another

## Chapter 2: Wind Power Generation

Modern wind power generation has its origins between the years 1850 and 1970, when the invention of the dynamo allowed for the conversion of kinetic energy of a wind flow to electric energy. Up until that time, wind power had aided industrial and agricultural processes such as milling and pumping since the ninth century. The first horizontal axis turbine, erected in 1887, was able to deliver 12 kW of power, the first megawatt scale wind turbine was introduced in 1941, and the first utility scale wind turbine was erected in 1978 in Denmark. A significant boost in the research and development into the wind power resource was driven by the oil crisis in the Middle East in the 1970's, aided partially by US government funding. The end of the 20<sup>th</sup> century, and the beginning of the 21<sup>st</sup>, interest in the wind power resource once again increased, the driving factor being the international effort to limit carbon dioxide emissions from fossil fuel power plants. The development of large scale wind power projects was incentivized with tax incentives and tariffs, stimulating additional research and development. Due to the ever ongoing research and development of wind turbines tailored to numerous applications, the costs have dropped significantly over the last decade (Breeze, 2016). In 2018, a subsidiary company of Nuon won a tender bid to develop the first offshore wind farm without the aid of government subsidies. The new wind farm should be operational by 2022 (Government of the Netherlands, 2018), indicating the enormous maturation the wind power resource has undergone in 50 years from the installation of the first utility scale wind turbine in Denmark.

## Technical analysis

The axis of rotation of the wind turbine blades can either be vertical or horizontal, and therefore two types of turbines can be identified: vertical axis- and horizontal axis wind turbines. Careful arrangement of the turbine blades allows for aerodynamic lift forces to be made significantly larger than drag forces. This is the main reason for the success of the horizontal axis turbine, opposed to its vertical axis counterpart (Fox, et al., 2007). Vertical axis wind turbines have proved to be not a commercial success

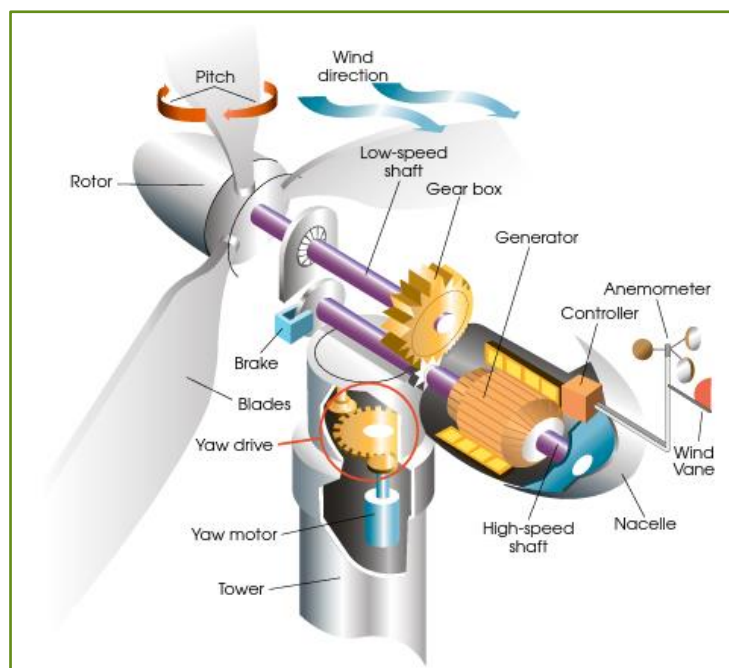


Figure 6: Main components of a typical modern high-power horizontal axis wind turbine (Lynn, 2012)

on large scale, however, a market for small scale vertical axis wind turbines still exists (Breeze, 2016). Figure 6 shows the main components of a modern horizontal axis wind turbine. These consist out of a rotor (usually two or three blades) on a shaft connected to a generator, either directly or with the intervention of a gear box. The rotor blades convert the translational kinetic energy of the air flow through the swept area into rotational energy transferred to the shaft, and a generator turns the rotational energy of the shaft into electrical energy, i.e. electricity. The most common version of the horizontal axis wind turbine is one with three blades since it is the optimum compromise between balance and cost.

Most grid connected wind turbines operate at a nearly constant rotational speed. Single speed wind turbines consist of an aerodynamic rotor, a low-speed shaft, a gearbox, a high-speed shaft and an asynchronous generator. The asynchronous generator, also referred to as an induction generator, is in direct connection to the power network. The variable speed wind turbine is designed to achieve maximum aerodynamic efficiency over a wide range of wind speeds (Hansen, 2017). The ratio of tip speed and wind speed is known as the tip speed ratio and is a commonly used variable in describing wind turbine operation. Within variable speed operation, continuous adaption of the rotational speed of the turbine rotor with respect to the wind speed allows for a constant tip speed ratio over a range of wind speeds. While the optimal operating range of a variable speed wind turbine is larger than that of a single speed wind turbine, the drawbacks of variable speed operation include the additional costs of the required power electronics, and their efficiency losses.

The performance of a wind turbine with regards to wind speed is described by the power curve, which enables a translation of the local windspeed to a power output rating. The exact power curve of a turbine is a distinct characteristic of the model (e.g. Figure 7); however, all power curves have a similar shape. The differences in power curve are most notably the rated power, cut in speed and rated speed. The slope and cut-out speed are nearly always similar, as indicated by Figure 8. Below the cut-in speed, the wind turbine remains inactive. From that point, for increasing wind speeds, the output power theoretically increases in a cubic relation to the wind speed. Above rated wind speed, the stance of the rotor blades is altered to limit its aerodynamic lift ability. As a result, the mechanical loads on the drive

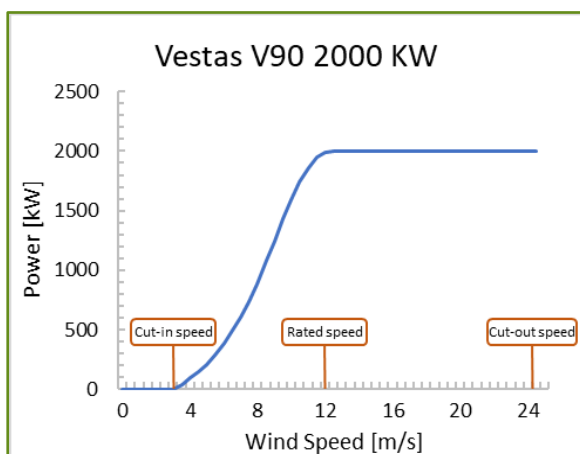


Figure 7: Single turbine power curve (Bauer & Matysik, 2018)

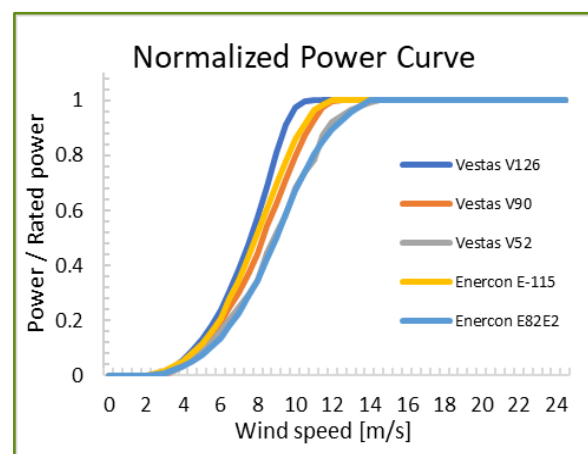


Figure 8: Comparison of the power curves of the five most common wind turbines in the Netherlands (Bauer & Matysik, 2018)

train do not exceed undesirable limits, and the power curve is horizontal from the rated wind speed onwards. At wind speeds of around 24 m/s (between 9 and 10 on the Beaufort scale, stormy conditions), the wind turbine cuts out, meaning the turbine blades are pitched sufficiently to generate no lift. This is referred to as the cut-out wind speed, and it is an important safety feature of modern day wind turbines.

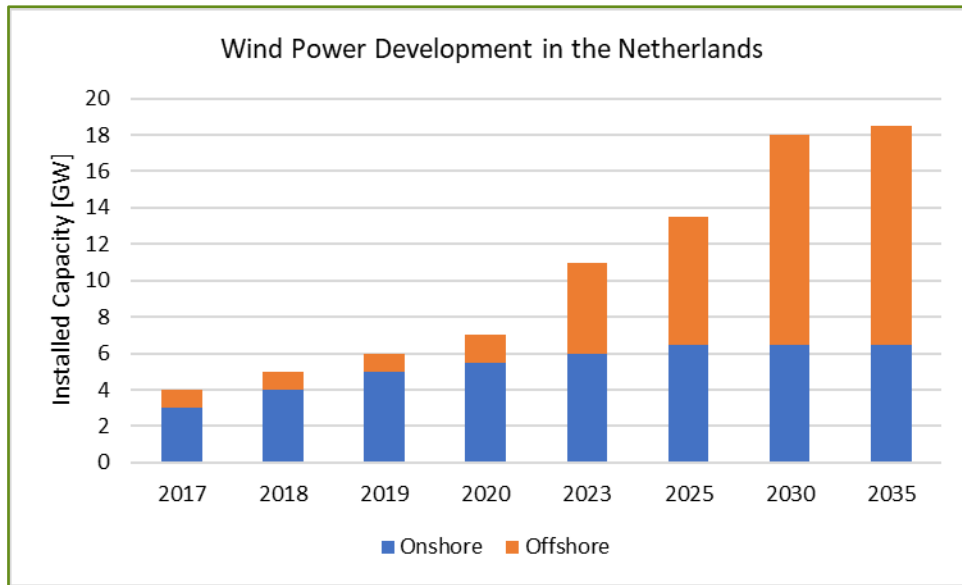
A grouping of several large turbines is known as a wind farm or wind park. The size of a wind farm varies from two or three individual turbines to more than a hundred capable of producing a combined power output of hundreds of megawatts. Such large wind farms require large, unobstructed windswept areas, either on land, referred to as onshore wind farms, or on large bodies of water, known as offshore wind farms. Location is key, regarding the development of a new wind farm. A prospective location must have high average wind speeds and are preferably reasonably close to existing grid networks. Ideal locations for onshore wind include farmland, since the wind turbines cause little disturbance to the day-to-day activity on the land, but also sides of motorways, canals and rivers where urban development is unlikely to take place (Letcher, 2017). Although onshore wind development is promising, factors such as noise pollution, safety and impact on wildlife must be considered. Development of offshore wind farms is mostly driven by the vast available geographic locations and an overall higher average capacity factor compared to onshore locations. The potential scale of offshore wind development is therefore enormous, however, connection to the grid poses major challenges.

## Wind power generation in the Netherlands

The state of wind power generation and its potential for future development has briefly been discussed in chapter 1. The aim of this section is to further analyze and quantify the current onshore and offshore generating capacity and their potentials for future development in the Netherlands.

Major market players in terms of turbine manufacturers are Vestas, Siemens, Enercon and Lagerwey. Pure in number of turbines installed, Vestas is the most common manufacturer in the Netherlands, seconded by Enercon. Their combined numbers represent nearly half of all turbines installed. The five most common onshore turbines in the Netherlands (in terms of manufacturer and power rating, not exact model) are Vestas 850, 2000 and 3000 kW turbines, and the Enercon 2350 and 3000 kW turbines (Bosch & van Rijn, 2018). The Vestas V90 model is one of the most used onshore wind turbine generators and is therefore depicted in Figure 7 as an illustrative example. Offshore wind turbines are generally larger and have a higher power capacity rating. The most common turbines Netherlands are Siemens 4000 kW and Vestas 3000 kW. Construction of new wind farms will see significant increase in the individual power rating.

Figure 9 is based on data from the Nationale Energieverkenning 2017 by ECN. From 2023, it is expected that the annual addition of onshore wind power capacity will decrease to zero in 2025 and onwards. However, currently and until that time arrives, onshore wind is the dominant source of renewable energy in the Netherlands. In 2013, the Dutch government and market parties drafted and signed the Energy Agreement. Regarding onshore wind energy, it was agreed upon that by 2020, 6000 MW of generating capacity must be operational. In 2017, only 3249 MW of onshore wind power was available, therefore a significant challenge lies ahead in reaching the 2020 goal. Onshore wind energy



*Figure 9: The role of onshore wind energy is expected to dominate offshore wind energy until 2023, at which point large offshore wind farms must be in operation based on current policy (ECN, 2017)*

is considered to be one of the most efficient and cost effective sources of renewable energy by the Dutch government (Rijksdienst voor Ondernemend Nederland, 2018a).

While onshore installed capacity in the Netherlands will still be equal to the offshore installed capacity in 2025, the offshore capacity is expected to grow significantly in decade thereafter. By 2035, the offshore installed capacity is expected to account for more than 60% of wind power generation and around 23% of the national installed power capacity (ECN, 2017). The average wind speed on offshore locations is generally higher than most onshore locations. Additionally, fewer objections are raised in the planning and development of offshore wind farms, an issue that onshore wind farms do face regularly. Currently, there are four existing offshore wind farms in the Netherlands: Egmond aan Zee wind farm, Prinses Amalia wind farm, Luchterduinen wind farm, and Gemini wind farm. The cumulative power of these four wind farms is equal to 957 MW. Future development of offshore wind farms in the Netherlands is driven by the Energy Agreement, signed by the Dutch government in 2013. It was agreed upon that five wind farms should be completed by 2023. The total installed capacity of the existing wind farms and the yet to be developed wind farms by 2023 must ensure 4.5 GW; and another 7 GW of additional installed capacity are prescribed in the roadmap towards 2030. The first round of tenders for this future development will start in 2019 with the Hollandse Kust (Noord) wind farm zone. The power capacity of a single wind turbine for future offshore development is more than twice that of existing offshore wind turbines. The turbines proposed for the Borssele Wind Farm Sites 1 to 4 are the Siemens' 8.0 MW Gamesa and Vestas' 9.5 MW V164 models (Rijksdienst voor Ondernemend Nederland, 2018b).

## Challenges associated with wind power

The main issue when connecting a wind turbine to the grid is power quality, referring to voltage and frequency stability and the absence of various forms of electrical noise, such as harmonic distortion or flicker (Bussel, Power Quality, 2008). Fixed speed wind turbines must be operated within 2 percent of the synchronous speed. Acceleration from rest therefore poses an issue. Regular starting of a wind

turbine would cause a local power dip since the magnetic field in the stator needs to be powered; followed by a power peak as the turbine starts to generate power. Therefore, start-up is usually achieved by electrically isolating the generator until the rotor achieves its rated speed. The circuit breaker consisting of a thyristor then allows for gradual connection to the grid. This is referred to as a soft start, and the reverse method is applied when disconnecting the turbine from the grid. There are three issues posed to the power quality of a wind turbine: dips, harmonics and flicker. One source of dips is the start-up of a wind turbine, where, if soft start is not properly applied or malfunctions, major power spikes or dips will occur. Another source of power dips in wind powered networks is the variability of wind speed. National standards defined in the grid code deal with load switching, however, the variable nature of wind speed requires other measures to counteract the effect on the power supplied by the wind turbine. A wind turbine requires multiple power converter units to operate at the rated voltage and frequency. These power converters are apt to generate harmonic voltage distortions. In general, power system planners will seek to ensure that installations do not worsen harmonics on the power system. Very small voltage distortion can cause large harmonic currents at a resonant condition. The detailed design of a wind farm must include measures to prevent harmonic signals in the operational voltage. Flicker is an engineering expression for short lived voltage variations in the electrical grid which may cause light bulbs to flicker for example. In the case of wind power generation, it is assumed that the phenomenon is (partially) caused by the passing of a turbine blade with the tower. The shielding effect of the tower reduces the torque output of the blade, resulting in a reduction of about 20% (Fox, et al., 2007). These issues related to the power quality of a wind farm are compensated for by additional power electronics. Energy storage systems have shown to be able to provide ancillary services to improve the power quality, reducing the need for additional power electronics.

The advent of wind power in the worldwide power production portfolio has led to certain stability issues in the provision of power within local grids. Until recently, wind farms were treated as non-flexible operating generators, and were therefore not responsible for active voltage or frequency control. Variation in grid voltage or frequency meant that wind turbines were required to disconnect from the grid. However, with the increasing share of wind power present in grid portfolios, disconnection or curtailment can lead to power mismatches. The intermittent and relatively unpredictable nature of wind requires careful monitoring and planning of dispatch. The unpredictability of wind elicits a backup power requirement in case of a mismatch in expected and produced power. Managing the alternative capacity in relation to the production of a wind farm remains one of the greatest challenges for wind power. Other challenges include the remote nature of suitable locations for wind power generation. The local demand of such areas such as offshore wind parks is minimal compared to the potential production capacity. Therefore, additional infrastructure in the form of transmission lines may be required to transport the energy to centralized substations. Focus remains on the main challenge of wind power grid integration, the balance of the grid. A conventional grid (without intermittent sources) has only the variability of the load to account for since conventional sources are more controllable in their output. The addition of intermittent sources causes an additional variability in in the grid, but on the production side. An unbalanced grid, on any scale, is defined as a mismatch between injection into the grid and uptake from the grid. Effects of an unbalanced grid, aside from not being able to meet the demand, is that voltage

and frequency deviations occur. A frequency or voltage deviation from the design conditions are known to be able to cause damage in the power plant equipment (Kouskou, Bruel, Jamil, El Rhafiki, & Zeraoui, 2014). Clearly, the integration of wind power within a grid is not trivial, and many factors need to be considered. The ability of a grid to handle large volumes of intermittent energy produced by intermittent renewable energy sources depends on the structure of the grid, and the supporting energy sources. A study by the International Energy Agency reported that the Danish grid could support 63% penetration of intermittent renewable energy sources in 2011 from a hardware point of view. The least flexible area identified (Japan) had a maximum possible penetration of 19%, and other areas range somewhere between 27% and 45% (IEA, 2011).

### Scope definition

Referring back to chapter 1, the scope has been limited to wind farms of a maximum generating capacity of 100 MW due to battery energy storage compatibility. The future of wind power generation is in offshore development, as indicated by Figure 9 and the underlying study performed by ECN. Offshore wind power development is characterized by larger individual turbine power capacity, as well as larger sites compared to onshore wind power. An overall offshore wind farm capacity is therefore multiple times larger than the largest onshore wind farm. Furthermore, the capacity factor of offshore wind energy is generally higher. However, challenges for offshore development include grid connection methods and complicated installation and maintenance. Onshore wind energy will steadily increase in generating capacity up to 2025, and therefore outweigh offshore capacity in that period. The order of magnitude of onshore wind parks corresponds with the 100 MW limit defined by the scope in chapter 1. Additionally, since net connections are already in place for existing wind farms and pose less of an issue compared to the offshore counterpart in the development of new wind farms, the potential of battery energy storage for the wind energy resource is best analyzed initially for onshore wind. Considering the storage requirement in terms of volume and duration, less complicated development and the novelty of the hybrid approach, this study will focus on onshore hybrid power plant optimization.

## ***Key Takeaways Chapter 2***

- The wind resource has been used to aid industrial and agricultural processes since the ninth century, but the most significant development in modern wind energy started in the mid-20<sup>th</sup> century
- The Netherlands will face significant development in onshore wind energy up until 2020, when the installed capacity must equal 6 GW
- In 2017, 958 MW of offshore capacity was operational, and per the Energy Agreement, 4.5 GW must be operational by 2023, and nearly 12 GW by 2030
- Connecting a wind turbine to the grid can cause voltage dips, harmonic voltage variation and a phenomenon known as flicker. Wind park design must include detailed measures to ensure a sufficient power quality
- For increasing levels of intermittent renewables in the power production portfolio, additional measures such as energy storage must be taken to ensure a continuous balance between injection to and uptake from the grid
- The focus of this study remains on mid- to large- size wind farms with a maximum generating capacity of 100 MW, corresponding to onshore wind power generation. Larger wind farms are expected to require large scale and long term energy storage solutions

## Chapter 3: Battery Energy Storage Systems

## Nomenclature and convention

A distinction is made between primary and secondary batteries: primary batteries are only able to convert the chemical potential of its cells to electrical energy and can therefore not be recharged, while secondary batteries allow for reverse operation. As a consequence, secondary batteries are also referred to as rechargeable batteries. For the purpose of utility scale energy storage, it is crucial that the system is able to recharge with the excess generated electricity (Huggins, 2016), and therefore secondary batteries are considered.

Battery electrodes can be referred to by their respective charge, either positive or negative. However, the electrodes in electrochemical cells are commonly referred to by 'cathode' and 'anode'. The cathode is the electrode where oxidation takes place, and reduction takes place at the anode. In case of a primary cell, where only discharge is possible, the cathode and anode constantly correspond with the positive and negative electrodes respectively. However, for secondary cells, oxidation takes place at the positive electrode during the discharge cycle, and reduction takes place at the positive electrode during charge (and the exact opposite is true for the negative electrode). In other words, while the charge of an electrode is constant for the charge and discharge cycle, the indication of cathode and anode switches between the electrodes (Glaze & Geniès, 2013). A comprehensive overview is presented in Table 1.

*Table 1: Cathode / anode convention for a secondary battery*

	<b>Charge Cycle</b>	<b>Discharge Cycle</b>
<b>Positive Electrode</b>	Anode	Cathode
<b>Negative Electrode</b>	Cathode	Anode

The capacity of a battery refers to the amount of energy that can be stored in the system. For small scale batteries required for portable electronics, it is common to refer to the capacity in ampere-hours. Primary alkaline AA batteries usually have a rating of 2500 mAh, meaning the cell can provide 2500 milli-ampere for one hour straight, or any other combination of current and time of which the product is 2500 mAh. Such a cell is usually rated at 1.5 volts, meaning the energetic capacity is 3.75 watt-hours. For larger systems, like those in EV's or stationary storage systems, a capacity rating is usually provided in kilowatt-hours. A 100 kWh battery system can provide 100 kW of continuous power for one hour. Charging and discharging rates are provided by the manufacturer which relate the power rating to the capacity of the battery system.

The state of charge (SOC) of a battery refers to the amount of available energy remaining in the cell compared to its rated capacity. It is therefore a dimensionless value, ranging from zero when fully discharged to one when charged to full capacity. Depth of discharge (DOD) of a battery refers to the energy extracted by a battery at any moment during a discharge cycle, compared to the rated capacity of the battery. Similar to the state of charge, the depth of discharge is a dimensionless value ranging from zero to one. The two are related by equation (3.1).

$$SOC = 1 - DOD \quad (3.1)$$

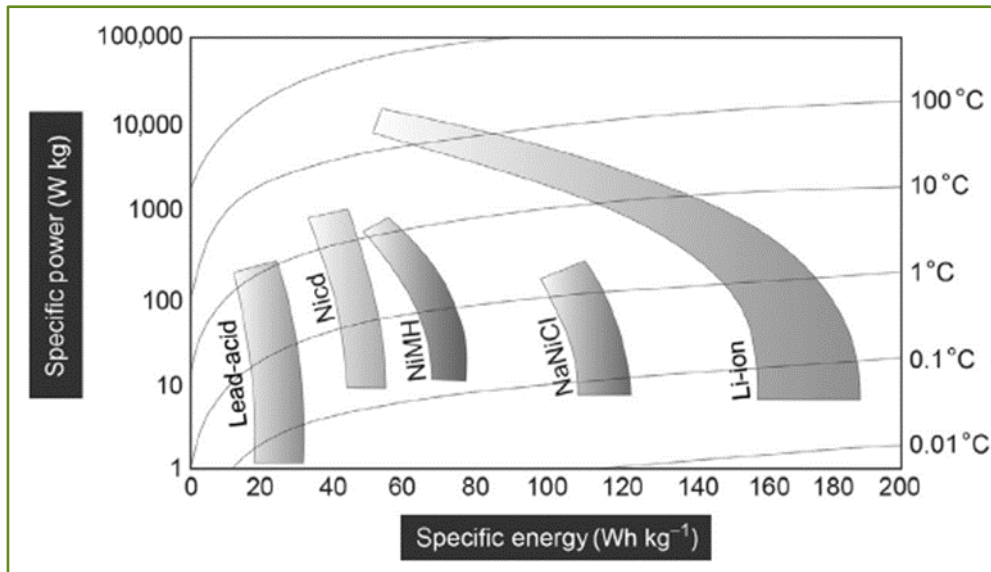


Figure 10: The high range of both specific energy and power make lithium-ion batteries suitable for a wide range of applications (Bresser, Paillard, & Passerini, 2015)

### Lithium-ion battery technologies and materials

Figure 10 shows the favorability of lithium-ion technology in terms of power and energy rating as compared to traditional lead-acid batteries, nickel based batteries and sodium-nickel-chloride batteries. Lithium-ion batteries are considered to be the most promising energy storage technology and show great potential in stationary energy storage as their cost continues to decrease and safety and cycling life are improved (Wang, Wang, Gordin, & Choi, 2010). Lithium-ion battery technology is widely used for portable electronics, EV and stationary energy storage. The working principle of this type of battery relies on reactions between positive lithium ions with metal oxides. The cathode consists of a lithium metal oxide, and the anode is made of a porous carbon structure. During charge, the positive lithium ions flow from the cathode, through the electrolyte, to the anode, where the ions are intercalated (inserted) in the porous structure of the carbon electrode. The reverse process takes place during the discharge cycle. The charge and discharge cycles are represented in Figure 11. Numerous lithium metal oxides are possible for the cathode; however, the anode is always a form of carbon. Advancements within this technology have resulted in a high cycling life from 3500 to as high as 10000 cycles. The overall efficiency of this technology ranges from 80 to 90%. Another important feature of this technology is the high energy and power density compared to the previously mentioned technologies. The main hurdle of lithium-ion batteries is the relatively high cost (Chen, et al., 2009).

The term lithium-ion battery covers all battery technologies that rely on the transport lithium ions from one electrode to the other. The electrode and electrolyte materials, as well as the crystal structure of the electrodes are crucial for the characteristics of the battery, and therefore the suitability of the battery for utility scale stationary energy storage. The cathode (positive electrode during discharge) of any lithium-ion battery is a metal oxide, the anode (negative electrode during discharge) consists of porous carbon. During discharge, the ions flow from the anode to the cathode through the electrolyte and separator, and the reverse reaction takes place during charge. The reactions that take place at the cathode and anode (oxidation and reduction) are referred to as half-reactions (Glaze & Geniès, 2013).

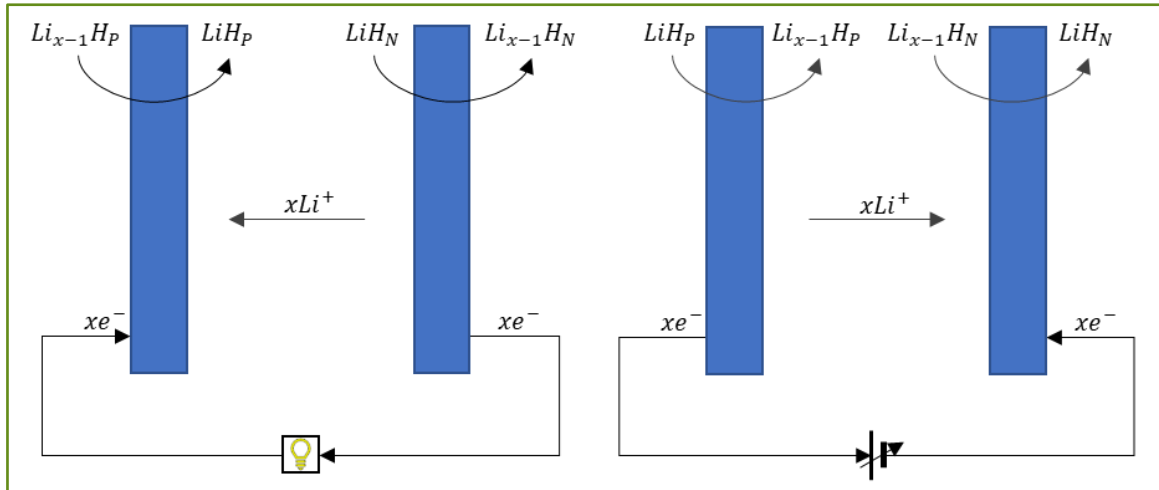


Figure 11: Principle of operation of a lithium-ion battery, with the discharge cycle on the left and the charge cycle on the right. The arrows represent the direction of movement of the charge

The overall reaction of a lithium-ion battery omits the lithium ions and electrons, since these are ‘cancelled out’ when combining the half reactions.



Equation 3.2 to 3.4 show the cathode and anode half-reaction and the overall reaction respectively. In these reaction equations,  $H_P$  and  $H_N$  refer to the positive and negative host material respectively. The forward reaction corresponds with discharge, whereas the reverse reaction corresponds with charging of the battery. The lithium ions are transported through the electrolyte, and the electrons through the external circuit. Figure 11 shows the half reactions for each electrode, both for the discharge as well as the charge cycle (Glaze & Geniès, 2013). Insertion and extraction of lithium ions in and out of the electrodes is referred to as intercalation and deintercalation. The ability of an electrode to uptake lithium ions therefore strongly determines the performance of a battery technology. A common anode material used to be coke, but currently most anodes consist of graphite due to favorable voltage ratings at low state of charge. It takes six carbon (graphite) atoms to bind one lithium ion, whereas a single silicon atom can bind to four ions. Three to five percent of silicon is usually added to the anode to enhance performance in terms of capacity. However, the growth and shrinkage of silicon as a cause of intercalation and deintercalation are reported to cause mechanical stress within the anode structure, resulting in increased degradation (Buchmann, 2018). The positive host material of the cathode is usually a lithiated metal oxide that exhibit a crystallized structure that offers one-, two- or three-dimensional paths for diffusion of lithium ion insertion. Three structures of lithiated metal oxides identified: lamellar-, spinel- and olivine-type crystalline structure, as represented in Figure 12.

In order to characterize the technologies discussed above, six performance indicators are identified and used in the graphics of Figure 14 to Figure 18. The overall score of a technology is determined by the area of the spider diagram. This score partially determines the suitability of a technology for utility scale

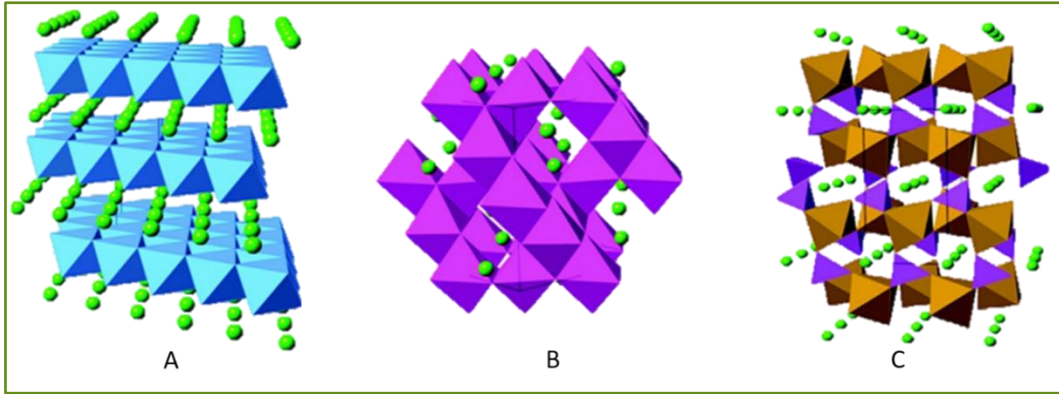


Figure 12: Crystal structures of representative intercalation cathodes. The lithium ions are represented by the green spheres, and the cathode material by the hexahedrons. A) Lamellar; B) Spinel; C) Olivine

stationary energy storage. The first indicator is *safety*, which seems trivial, but since many applications of battery energy storage exist, safety is considered differently for each specific case. The main concern regarding safety is thermal runaway. This phenomenon refers to a mechanism where increased operation temperatures cause a chain reaction of further increasing temperatures, and eventually failure (Feng, et al., 2018). Systems with high risks of thermal runaway will require additional cooling installations and precise state of charge monitoring. The second indicator is the *life span* of the technology. There are two aging mechanisms regarding all batteries: calendar aging and cycle aging. The former refers to battery degradation as a cause of stationary deployment, whereas cycle aging refers to degradation as a direct cause of charging and discharging. Third, *performance* of a battery can be characterized according to the batteries' functionality over a large range of temperatures. The fourth and fifth indicators are *specific energy* and *specific power*, in watt-hours per kilogram and watt per kilogram respectively (also indicated in ampere-hour per cubic centimeter and ampere per cubic centimeter). It is an indication of the compactness of a cell with a given energy or power rating, either in terms of weight or in terms of volume. These indicators are especially relevant for portable electronic devices where compactness is a key parameter, and EV, where both battery volume and weight are crucial in the design of the vehicle. In the case of stationary energy storage, especially in combination with wind farms, the spacious constraints are less critical. The sixth and final indicator is *cost*, which is determined by the (fixed) capital cost and (varying) operational cost. Since the cycling of a battery leads to degradation, the value of total energy stored and discharged by the battery should be considered when comparing costs of different technologies. The Levelized Cost of Storage (LCOS) is an intuitive marker for cost comparison in batteries.

$$LCOS = \frac{\text{Total cost of system}}{\text{Cumulative volume of energy stored}} \left[ \frac{EUR}{MWh} \right] \quad (3.5)$$

The spider diagrams used in this section give an estimation of these indicators. A high value of one of these indicators means it is a favorable characteristic of the respective technology (a high score on cost means the cost is relatively low).

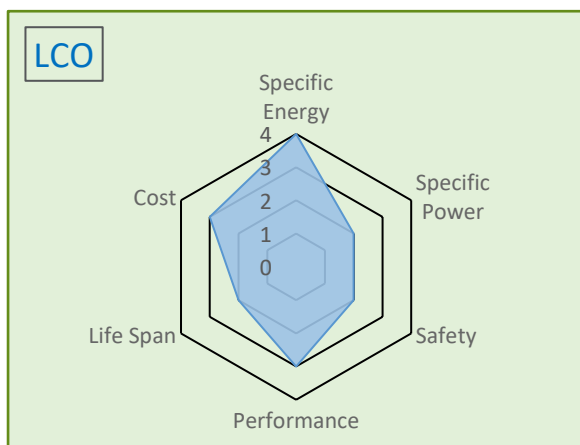


Figure 14: LCO technology is characterized by high specific energy, but life span, safety and power capacity are causes for limited deployment

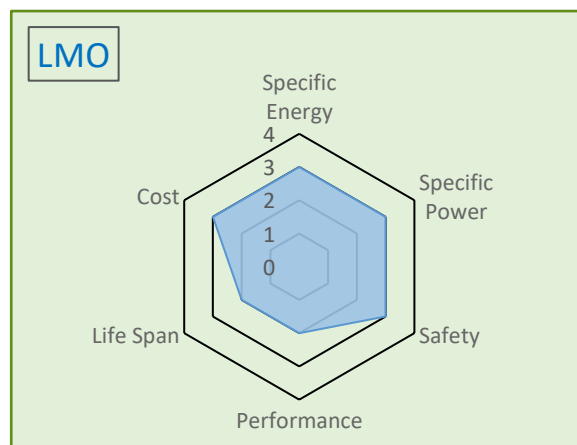


Figure 13: LMO technology is the preferred choice for power tools, among others. In combination with NMC, it is also applied to EV's. The increased thermal stability leads to a higher safety rating than LCO

### Lithium Cobalt Oxide ( $LiCoO_2$ ; LCO)

The name of this first technology refers to the cathode material of the cell, lithiated cobalt oxide. The cathode consists of a lamellar structure of cobalt oxide, with the lithium ions intercalated between these layers. The ions move from the graphite anode to the cathode during discharge (Buchmann, 2018). It is a very attractive cathode material due to the high theoretical specific capacity of 274 mAh/g, high theoretical volumetric capacity of 1363 mAh/cm<sup>3</sup>, low self-discharge, high discharge voltage and good cycling performance (Nitta, Wu, Lee, & Yushin, 2015). Therefore, it is a technology actively deployed in portable electronics. However, these characteristics are overshadowed by a short lifetime, low thermal stability, and limited load capabilities.

### Lithium Manganese Oxide ( $LiMn_2O_4$ ; LMO)

This technology relies on a spinel structure, in contrast to the previous battery which relied on a lamellar structure. The result is a three-dimensional manganese oxide structure of the cathode, improving ion flow and thereby lowering internal resistance and improving current handling. Another improvement compared to LCO is the increased thermal stability. Another improvement compared to cobalt- or nickel-based batteries is the low toxicity of manganese (Nitta, Wu, Lee, & Yushin, 2015). The applications of this technology include power tools, medical devices and electronic powertrains, though usually in combination with other cell technologies to improve performance (Buchmann, 2018).

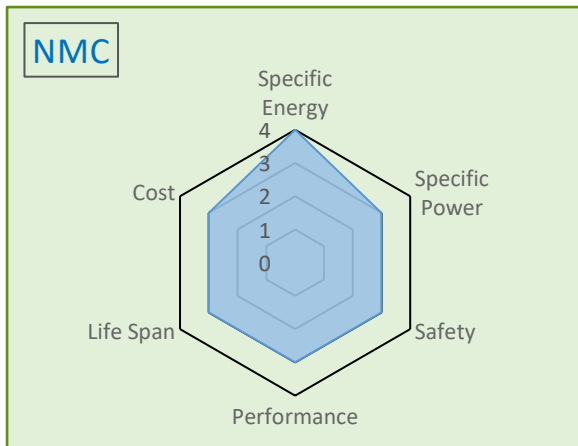


Figure 15: NMC scores well across all indicators. It is the leading battery technology in electric vehicles. Increased demand for EV leads to technological development in the battery technology, and with it cost reduction

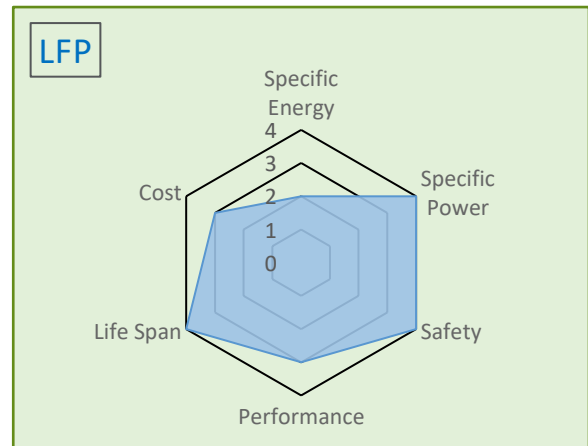


Figure 16: Due to its high power and load current capacity, this technology is preferred for high load applications. Its low specific energy is no issue for stationary storage but limits its' use as an EV battery.

### Lithium Nickel Manganese Cobalt Oxide ( $LiNiMnCoO_2$ ; NMC)

This is one of the most successful lithium-ion technologies, applied in mid- to large size energy storage systems, such as EV's, some medical devices, and industrial applications (Buchmann, 2018). It has similar or even higher achievable specific capacity than LCO and similar operating voltage. Furthermore, the cost is reduced, since the cobalt content is reduced. The theoretical specific and volumetric capacity of the NMC battery is 280 mAh/g and 1333 mAh/cm<sup>3</sup> respectively, which is comparable to LMO, but the thermal stability, increased life span and cost reduction make NMC the preferable choice for applications outside of portable electronics (Nitta, Wu, Lee, & Yushin, 2015). Overall, NMC is today certainly the most suitable lamellar cathode material, offering the best compromise in terms of specific energy, cycling performance, cost, and thermal stability (Bresser, Paillard, & Passerini, 2015).

### Lithium Iron Phosphate ( $LiFePO_4$ ; LFP)

Lithium iron phosphate offers good electrochemical performance with low resistance, and with it a high current rating and long cycle life. The technology is characterized by an olivine structure, in contrast to the previously mentioned layered and spinel structures. This technology is known for its' thermal stability and a high power capability. However, a major drawback is the relatively low average voltage potential and low electrical and ionic conductivity (Nitta, Wu, Lee, & Yushin, 2015). Applications of LFP include portable and stationary appliances requiring high load currents and endurance, such as starter batteries for cars, as well as stationary storage applications (Stan, Swierczynski, Stroe, Teodorescu, & Andreasen, 2014).

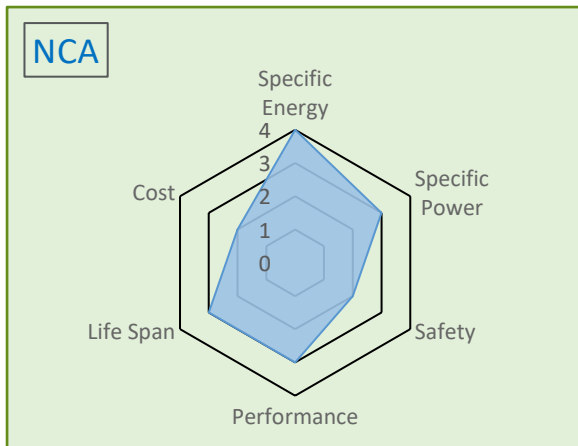


Figure 17: Even though the specific energy and power are relatively high, NCA is not the preferred choice for many applications due to the high costs and lower safety compared to NMC

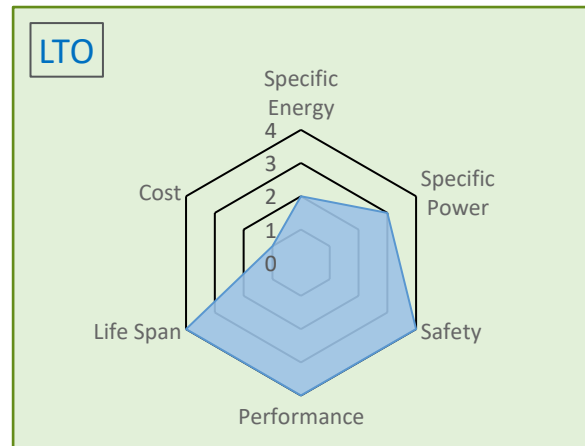


Figure 18: LTO is characterized by high specifications regarding performance, life span and safety. However, the high material costs and relatively low specific energy limits its current use.

### Lithium Nickel Cobalt Aluminum Oxide ( $LiNiCoAlO_2$ ; NCA)

This technology shares similarities with the previously discussed NMC, offering high specific energy and power. It has found widespread use in EV batteries due to the high usable discharge capacity and long storage calendar life compared to conventional cobalt-supported structures (Buchmann, 2018). However, it is reported that capacity fade at elevated temperature is severe due to solid electrolyte growth and micro-crack growth at grain boundaries (Nitta, Wu, Lee, & Yushin, 2015).

### Lithium Titanate ( $Li_4Ti_5O_{12}$ ; LTO)

The final technology is lithium titanate, which refers to the material used in the anode (where the previous technologies referred to the cathode material). Spinel structured lithium titanate replaces the graphite in the anode of a typical lithium ion battery (LMO or NMC). Such batteries are mainly characterized by high safety and life span, since no solid electrolyte interface formation occurs, and thermal stability is higher than with other technologies. The stability is achieved since intercalation occurs with 'zero-strain', since there is little volume change at lithiation and delithiation. However, the battery is expensive, and the specific energy is low (Nitta, Wu, Lee, & Yushin, 2015).

Six lithium-ion material technologies are discussed but not all are suitable for stationary storage applications. Reduced safety and the risk of thermal runaway cause LCO and NCA to be less favorable, and both LCO and LMO have relatively low cycling life. Extreme costs are a bottleneck for the otherwise promising LTO technology. The two remaining technologies, NMC and LFP, are promising candidates for utility scale stationary energy storage.

### Technical parameters for system control and modelling purposes

Although lithium-ion batteries have favorable characteristics for fast and powerful discharging, there are limitations to the behavior. It is crucial to capture these limitations in parameters that can be used in the control of the hybrid power plant, as well as for modelling and optimization purposes. Parameters that influence the applicability of the battery system are charge and discharge rates, power and energy rating, efficiency, depth of discharge, voltage, maximum continuous discharge current, and maximum

thirty-seconds discharge pulse current (MIT, 2008). Since batteries are electrical devices, the specifications are usually presented in electrical quantities such as current, voltage and resistance by the manufacturer. Cycle aging is affected by temperature, depth of discharge and operating current. In general, lower operating temperatures, limited depth of discharge, and low C-ratings reduces cycle aging and prolongs battery life (Wang, et al., 2014).

### C-rate

The charge and discharge rate is referred to as the C-rate of a battery. The capacity of a battery in ampere-hours is usually rated at 1C, meaning a 2Ah battery can provide 2 amperes continuously for one hour. The same battery discharging at 0.5C (or C/2) will provide 1 ampere for two hours, and so on. The charging rate has a strong influence of the cycle aging of the battery, high discharge rates cause faster degradation (Broussely, et al., 2005). Equation 3.6 describes the relation between the C-rate, the power rating and the energy capacity of a battery.

$$C = \frac{\text{Power rating}}{\text{Energy capacity}} \quad (3.6)$$

### Power and energy ratings

The power capacity or power rating of an energy storage system denotes the maximum power that can flow into or out of the system at any given moment, measured in kilowatts. The energy rating of an energy storage system states how much energy the system is able to store, measured in kilowatt-hours. A given battery capacity, either in the specifications or in literature, refers to the energy rating. Since batteries have a wide range of applications, a specific use case may require different power and energy ratings than other cases. If the battery system is used primarily for ancillary services such as frequency and voltage regulation, then the system will often be required to provide short bursts of power. This use case demands a battery system with a high power rating, while a relatively low energy rating will suffice, resulting in a high power-to-energy ratio. If the battery system is used for peak shaving of wind power or solar PV systems, the system will have to provide power over a prolonged period, and the required power-to-energy rating is lower than for ancillary services (McLaren, 2016).

### Roundtrip efficiency

Lithium-ion batteries are characterized by high efficiencies, reaching values of more than 90% depending on the active materials and topology. Battery technologies that use insertion or intercalation generally have high efficiencies since these mechanisms do not involve breaking or forging chemical bonds but rather electrostatic interactions between the lithium ions and the crystalline structures. The efficiency of a complete charge/discharge cycle, referred to as roundtrip efficiency, depends on the operating conditions (current strengths, temperature and depth of discharge) and the electrode material. At low temperatures, low current strengths and low depth of discharge, the roundtrip efficiency approaches its maximum value. Equation 3.7 states that the roundtrip efficiency is equal to the product of the charge- and discharge efficiency.

$$\eta^R = \eta^C \eta^D \quad (3.7)$$

## Depth of discharge limit

Aging of a battery is described as the result of loss of reversibility in the active materials. Several mechanisms are responsible for this loss of reversibility. The porosity of the electrodes is recognized as one of the first order parameters controlling the capacity fade. 'Clogging' of pores by lithium metal deposition reduces the surface area of the active material (Broussely, et al., 2005). Charging in lithium-ion batteries is governed by intercalation. Deep charging and discharging may lead to overfeeding of the electrodes, causing metallic lithium build-up resulting in lithium plating (Buchmann, 2018). The battery life will increase significantly if the depth of discharge is limited to 80% of the rated capacity of the battery (Albright, 2012).

## Voltage ratings

Another relevant parameter of a battery is the voltage rating, and several terms regarding voltage may be found in literature or technical specifications. The nominal (rated) voltage of a battery is the mid-point voltage between full charge and full discharge and is a good indication of the operational voltage. The cut-off voltage is the voltage of the battery that determines the empty state of a battery. The terminal voltage of a battery is the voltage between the battery terminals with load applied and varies with SOC and discharge/charge current. The open-circuit voltage is the voltage between the battery terminals with no load applied and increases with SOC (MIT, 2008).

## Maximum current

Battery manufacturers define maximum allowable current loads to prevent excessive discharge rates that would damage the battery or its capacity. A distinction is made between continuous load currents and pulse currents. The maximum discharge pulse current is higher than the maximum continuous discharge current but may only be sustained for a finite (short) period. These maximum currents can be expressed using the C- and E-rates, since they are capacity dependent. As with the power, energy and voltage ratings, the maximum current is provided by the manufacturer.

## Battery system costs

Data regarding the cost breakdown of lithium-ion batteries obtained from literature and technical reports is presented in Figure 19. It is difficult to provide an exact, detailed cost breakdown, since manufacturers are not generally open with this data. This results in a relatively large variation between the analyzed sources presented in the figure. In all cases though, the material costs account for 50 to 55% of the total cost (when including housing within the material costs). The additional consist of labor, overhead and a profit margin. Among the rest remain items such as depreciation, warranty and utilities. The principal contributor of the material costs are the active cathode and anode materials (except in the case of the breakdown obtained from Lowe, where the power electronics are considered to categorize under 'other materials'). The cathode (during discharge; also known as the positive electrode, see Table 1) material cost contribution ranges from approximately 20 to 45% and the anode contribution ranges from approximately 7 to 20%. The reason for the significant contribution of the cathode is the fact that the active materials such as manganese are cost intensive compared to the anode material (carbon). It is expected that for increasing energy densities due to technological advancement, the share of

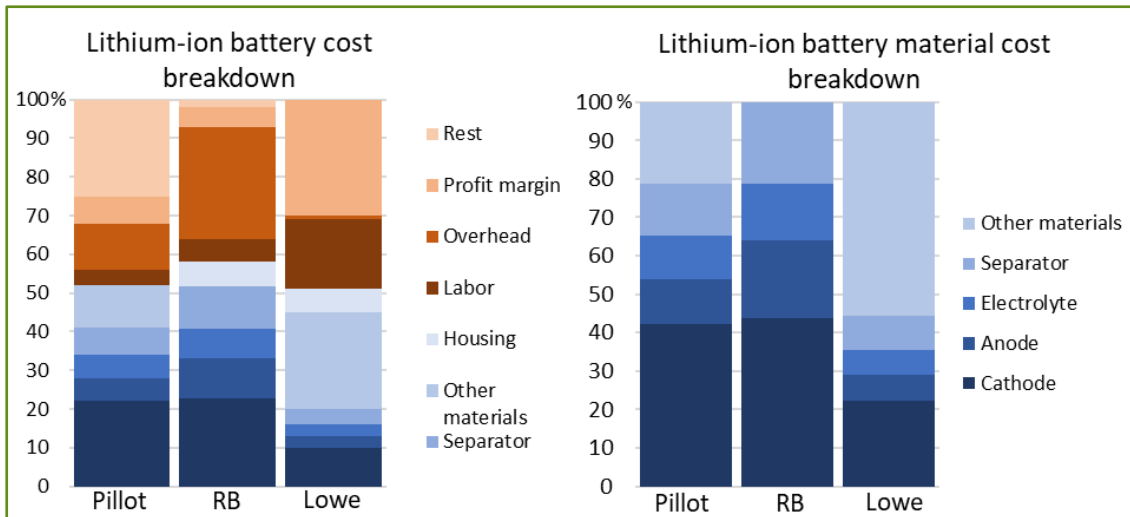


Figure 19: Cost breakdown of lithium-ion batteries, after (IRENA, 2017). Data obtained from (Pillot, 2017), (Roland Berger, 2012) and (Lowe, 2010), respectively

material costs will drop and therefore represents a significant cost reduction opportunity. The significant share of 'other materials' presented in the study of Lowe is caused by the fact that electrical components are categorized as such. The main message is the fact that all three studies obtain a similar share of material costs in the total cost of a battery system.

An extensive study has been executed by the International Renewable Energy Agency regarding energy storage costs. Since the electrode materials, and especially the active material of the cathode, represents the most significant part of the total system cost, an individual energy installation cost can be identified for each technology. The energy installation costs (in  $\frac{USD}{kWh}$ ) are presented in Table 2 for a current (2016) and future (2030), and worst, reference and best case scenario (IRENA, 2017). A quick comparison between the values in Table 2 and the spider diagrams in Figure 14 to Figure 18 shows no serious discrepancies. However, the price rating of NCA in Figure 17 is 1 on a scale of 0 to 4 (indicating an unfavorable price), while Table 2 indicates a reasonable price compared to the other technologies. This inequality may be explained by the requirement of additional safety measures, while the data in Table 2 only considers the installation cost of the energy storage system.

Table 2: Energy installation cost in [USD/kWh] (IRENA, 2017)

		Worst	Reference	Best
NMC & LMO	2016	840	420	200
	2030	335	167	79
LFP	2016	840	578	200
	2030	326	224	77
LTO	2016	1260	1050	473
	2030	574	478	215
NCA	2016	840	352	200
	2030	347	145	82

## ***Key Takeaways Chapter 3***

- Secondary batteries can fulfil ancillary services and serve an important role in the planning and operation of an intermittent power plant such as a wind farm
- Lithium-ion battery systems are the preferred choice due to their wide range of energy and power ratings and high overall efficiency
- A battery technology is referred to by its active material of the electrodes. The negative electrode material in lithium-ion batteries is a porous form of carbon. The positive electrode material is usually a lithiated metal oxide and determines the characteristics of operation
- Two specific technologies have been identified as applicable to utility scale energy storage: lithium-iron-phosphate (LFP) and nickel-manganese-cobalt-oxide (NMC) due to their overall score on six indicators
- The required power-to-energy ratio is strongly related to the use case of the battery system. High ratios are demanded by ancillary services, while peak shaving requires a lower ratio
- Safe and prolonged operation of battery energy storage systems require careful attention to the applied conditions such as depth of discharge and voltage and current ratings
- Active electrode materials are the main contributors to the total cost of a battery cell. Additional system costs include labor, overhead and the profit margin

## Chapter 4: The Dutch Power System

## Power system design

The Dutch power market was liberalized and restructured in 2004, causing a separation within the electricity system. Different actors are now responsible for different parts of the system. A distinction is made between the physical, technical layer of the electricity system, and the institutional layer of the system, as indicated in Figure 20. The technical layer consists of the physical chain, containing power plants, transmission and distribution networks and the ‘consumer’, or load. The institutional layer consists of actors responsible for the operation of the electricity value chain (electricity market). This chapter will provide an overview of involved parties and their place within the electricity system, as well as an overview of the trading schemes in the system.

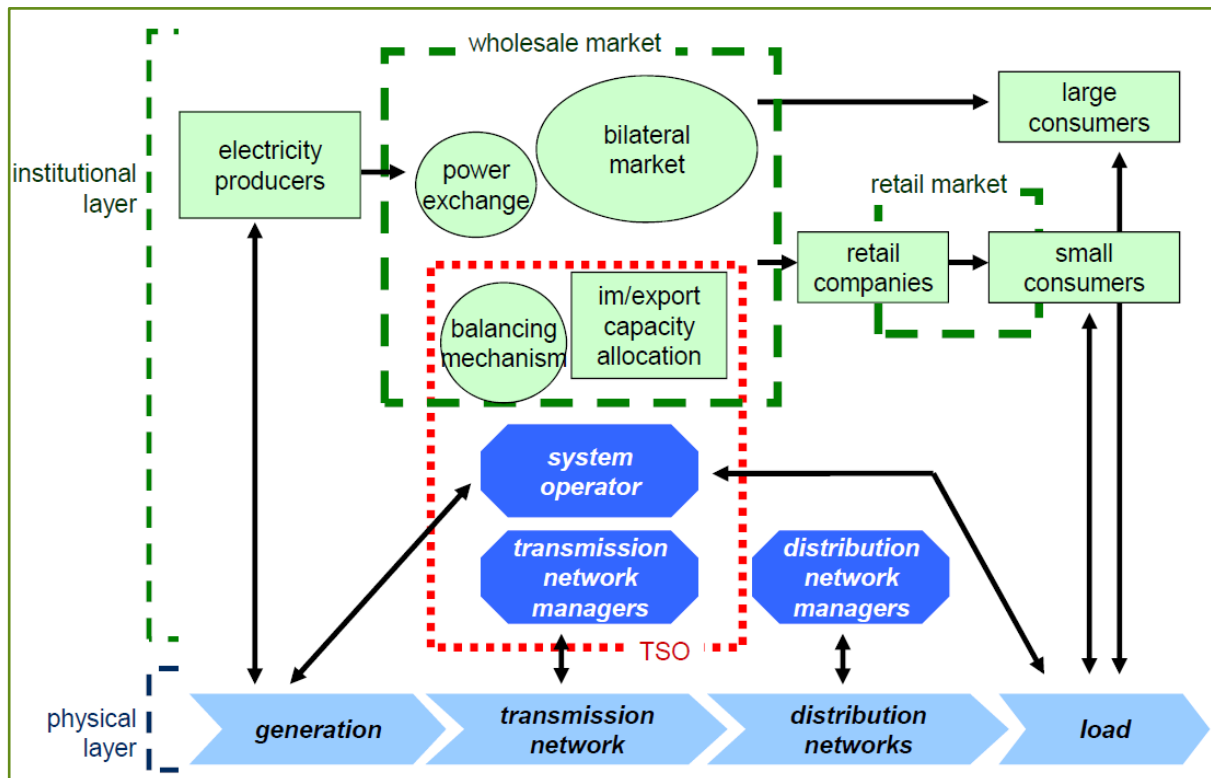


Figure 20: Representation of the Dutch power system and the distinction between the two layers. Single-point-arrows indicate the direction of the trade in electricity. Double-point arrows indicate the responsibilities of the institutional layer regarding the physical layer (de Vries, 2018)

## Generation

Electricity is produced in power plants with the aim to match a pre-defined commitment. This commitment emerges from bilateral long-term contracts or is based on a production program submitted to the power exchange (Day Ahead Market, to be discussed in the next section). All users of the Dutch electricity system, both generation as well as consumption, are program responsible, meaning the submitted schedule is to be followed. The responsibility may be exerted to a recognized program responsible party (PRP), which pools energy programs on behalf of all its' users to the Transmission System Operator (TSO). In Figure 20, the power plant falls under the physical layer, whereas the party responsible for the production of the power plant is part of the institutional layer.

## Program responsible parties

All parties participating in the production or consumption of electricity are program responsible. The obligations of individual parties may be pooled and transferred to a third party (natural or juridical person) referred to as the program responsible party. The generating or consuming party that transfers its responsibility to a PRP must report this transfer of responsibility to the TSO. PRP's operate within specific rights corresponding to the legal agreement between the PRP and the generating or consuming party. Among others, these rights include the submission of energy programs on behalf of the first party, as well as acting as a transaction party in settlement (ACM, 2015). These PRP's are responsible for the purchase of electricity and must maintain balance between the consumed and purchased electricity within their own portfolio. The pooling of many end consumers leads to predictable load behavior as opposed to single household consumption. The TSO will settle a mismatch between purchased and consumed electricity financially.

## Transmission System Operator

The TSO has three tasks, (1) to balance the injections and withdrawals of power in the transmission network, (2) to manage the electricity transmission network and (3) to manage (cross-border) import capacity. In the Netherlands, TenneT TSO B.V. is the only TSO, operating the 110 kilovolt network of more than 10,000 km in length (NEXT Kraftwerke, 2018). The European power grid depends on a 50 Hz AC frequency for the use of all electrical systems. Deviations from this frequency in one of the five European Network of Transmission System Operators for Electricity (ENTSO-E) areas can lead to power failures and blackouts. Imbalance between injections and withdrawals of power in the network

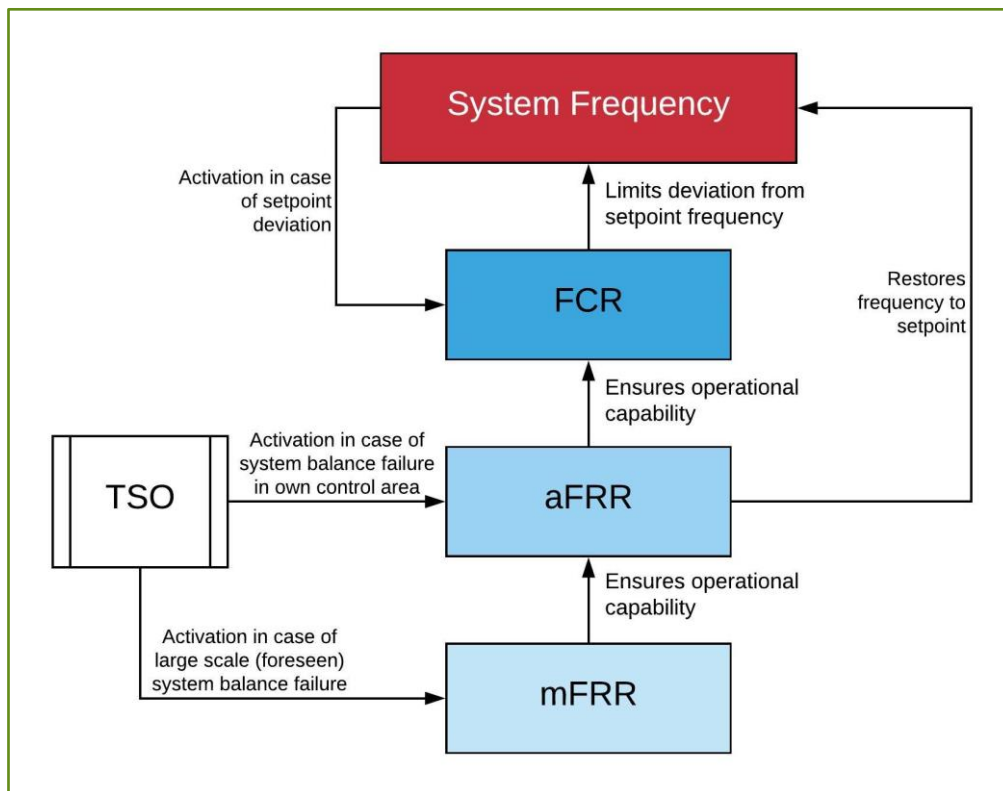


Figure 21: Balancing mechanisms employed by the TSO, in this case TenneT NL specifically. Figure based on (Consentec, 2014)

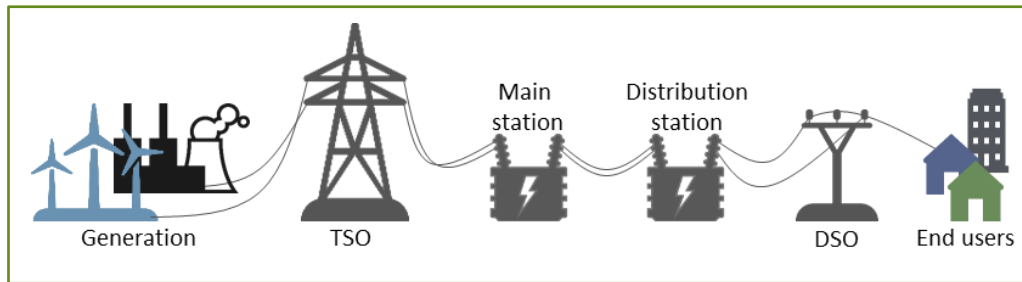


Figure 22: Technical overview of the power system from generation to consumption

are one of the sources of such frequency deviations, and the first task of a TSO is to maintain this delicate balance. Fluctuations in supply and demand are managed through tools such as regulating capacity, reserve capacity and emergency capacity (ACM, 2015). The responsibilities and mechanisms maintained by TenneT are schematically presented in Figure 21. If a setpoint deviation occurs in the system frequency, the Restoration Reserve (FCR), or primary reserve, is activated to limit this deviation. The Automatic Frequency Restoration Reserve (aFRR), or secondary reserve, is activated by TenneT to ensure the operating capability of the primary reserve, and to restore the system frequency to setpoint. The tertiary reserve mechanism is known as the Manual Frequency Restoration Reserve (mFRR) and is activated by TenneT in case of large scale system balance failure to ensure sufficient operating capability for the secondary reserve. Large scale energy storage is known to be complicated, but studies have shown that (distributed) energy storage can provide valuable services to the TSO for frequency regulation and other ancillary services (Staffell & Rustomji, 2016; Dicorato, Forte, Pisani, & Trovato, 2012).

### Distribution network operators and consumers

The distribution network operator (DSO) is the link between the high voltage transmission network operated by the TSO and the end user. The main task of a DSO is to distribute the electricity to the end-users. Accordingly, the monitoring and operation of the low- and medium-voltage capacity in their assigned region falls under their responsibilities. While power is transported over the high voltage network at 110 kV, the net voltage for most consumers is rated at 230 V. Figure 22 gives a schematic representation of the transport and transformation path between the generating and consuming parties.

### Electricity markets

Figure 20 shows the wholesale and resale market within the green dotted lines. The power produced in a power plant is sold on the wholesale market, either directly or with the intermission of a third party PRP. However, several submarkets can be distinguished, each with individual characteristics. An overview of these markets is presented here.

### Bilateral Agreements

The largest volume of produced electricity is traded based on bilateral and ‘over the counter’ agreements. Large producers and consumers negotiate contracts of delivery or consumption of power somewhere in the future. A good example of such a contract is the deal between Eneco and the Dutch railway organization, NS. The two companies claim that all Dutch trains run on wind energy, which technically is not true since the overhead lines are not directly connected to wind parks. However, in

2014, they negotiated the then largest energy contract in the Netherlands: the NS requires 1.3 TWh a year (NS, 2017) and will compensate Eneco for the production and delivery of this volume of wind energy to the European net. Such bilateral trade agreements are usually confidential (the compensation method between NS and Eneco is not publicly known either), but 85% of all electricity is accounted for by these agreements. The advantages of these agreements include adequate demand as well as risk reduction regarding volatile power prices (Ly, 2018).

## Spot Market

The remaining share of electricity is traded on the spot market, managed by the European Power Exchange (EPEX SPOT SE). The power exchange facilitates the transaction of power and provides trading platforms for power suppliers and consumers in Germany, France, the United Kingdom, the Netherlands, Belgium, Austria, Switzerland and Luxembourg. The Dutch power exchange is known as EPEX Netherlands, formerly APX Power NL. In the Netherlands, power is traded through a daily auction known as the Day Ahead Market, as well as real time on the Intraday Market. The core activity of the market facilitator is to compare the received generation and load bids, and to calculate the corresponding market price for each hour. The results are published one or two hours after closure of the bidding process. The bidding process is anonymous, but the market results are published and may serve as a reference to the bilateral market. If the power generating party is unable to meet its obligation established by an accepted bid, it must be compensated for on the imbalance markets. Figure 23 and



Figure 23: 17th of October 2018. A single day representation of the APX market volumes and prices. The horizontal axis represents the time of day, the primary vertical axis shows the total volume, and the secondary vertical axis shows the market price for each hour of the day (EPEX Spot, 2018)



Figure 24: 2017/2018 monthly average Day Ahead Market results as of October 1st, 2018. Primary vertical axis (left) corresponds to the total volume, and the secondary vertical axis to the electricity price (EPEX Spot, 2018)

Figure 24 show the market price developments over a single day and a full year respectively. Prices range from 40 to 65 EUR/MWh on average but can be much higher in case of low national production capacity as shown in Figure 24. The Intraday Market offers the opportunity to continuously trade power products in hourly intervals as well as freely definably block orders up to 5 minutes prior to delivery. Access to these markets is limited to members of EPEX Netherlands.

### Balancing Mechanisms

The first task of the TSO is to balance the injections and withdrawals to and from the grid as to assure a 50 Hz net frequency. In case of deviation of this EU wide net frequency, the TSO has the option to call upon reserve capacity and regulating capacity.

The primary reserve that TenneT NL can employ is the Frequency Containment Reserve (FCR). The goal of this reserve is to stabilize frequency disruptions in the internationally coupled grid. Generating and consuming parties have the option to offer a reserve capacity on a weekly basis, with a minimum capacity and step size of 1 MW. TenneT compares the received bids and selects a number of these bids which have the obligation to be available. Bidding parties are compensated for their offered capacity. The bids that are rejected have no obligation to the TSO. During the availability period of the bids, TenneT may activate the reserve capacity, and the supplier must fulfill this obligation within 30 seconds of that moment. The reserved capacity must be available for at least 15 minutes, after which a restoration time of two hours is maintained. The offered capacity must once again be available after the restoration time. There is a possibility that TenneT may not call upon the offered reserve. The supplier is still compensated for the accepted bid and must maintain the offered capacity readily available throughout the contracted period. The average capacity price on the 17<sup>th</sup> of October 2018 (the same day as depicted in Figure 23, for comparison) was approximately 2750 EUR/MWh. Currently, the contracted period is one week, but this is likely going to change to a single-day system as proposed by TenneT.

The reserves formerly known as the secondary and tertiary reserve are now called Automatic Frequency Restoration Reserve (aFRR) and Manual Frequency Restoration Reserve (mFRR). The

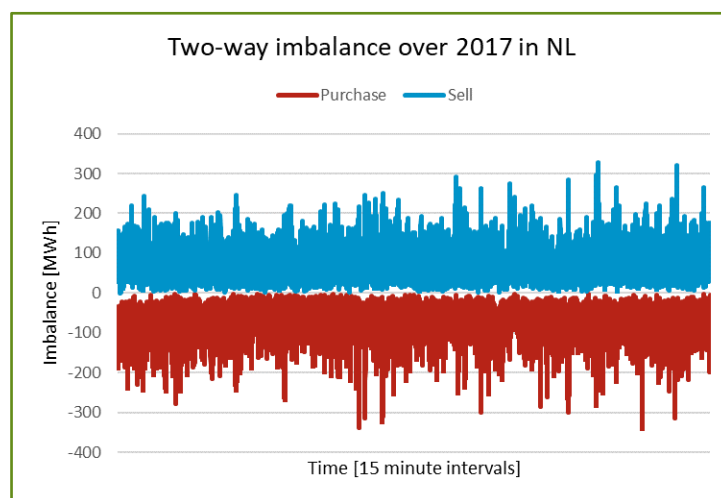


Figure 25: Imbalance over 2017, as monitored by TenneT. 'Purchase' refers to a shortage on the net, whereas 'sell' refers to a surplus on the net (TenneT, 2018)

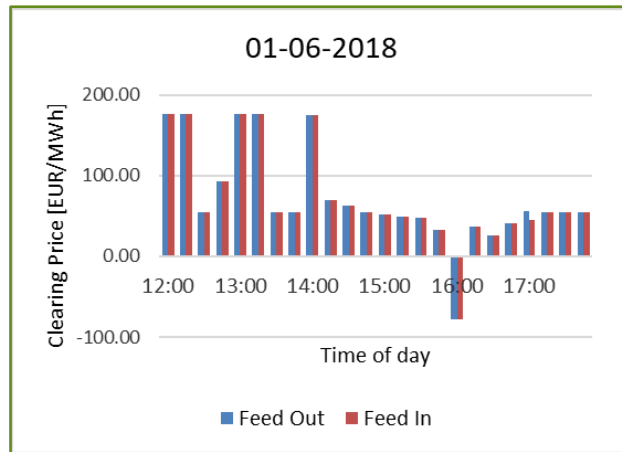


Figure 26: Imbalance prices on July 1st, 2018. Note that the Feed Out and Feed In prices are usually equal, with a single exception during these hours of this specific day (TenneT, 2018)

FRR is used exclusively for correcting real-time power imbalance throughout the net. The process of establishing an aFRR market is driven by imbalance between supply and demand to and from the net. Compensation prices for up- or downward regulation is therefore highly volatile and may contain large price-peaks throughout the day. The reason for the highly volatile market price for imbalance is illustrated in Figure 25, where the volumes of upward and downward regulation is given for the year 2017. The bidding process ends 60 minutes before the time of delivery (setpoint). Parties may offer upward or downward bids of at least 1 MW, with a step size of 1 MW. TenneT is responsible for collecting, accepting and rejecting the bids and will determine the settling price per MWh based on the accepted bids. Parties responsible for the accepted bids must be able to offer up and down ramp rates of at least 7% per minute at the time of delivery, and an observable power change is expected within 30 seconds after the setpoint. Figure 26 shows the imbalance prices, where 'Feed Out' refers to purchasing power from the net, and 'Feed In' refers to selling to the net. These prices will be referred to as the imbalance prices of power. The imbalance price is established for each 15-minute interval. Access to the mFRR is limited to suppliers that can offer at least 20 MW of emergency power, whereas the minimum capacity and step size for aFRR is 1 MW. The use of the emergency power (mFRR) may last as long as several hours.

### Identification of accessible markets

Accessibility for the proposed hybrid power plant of the available markets relies on a couple of criteria. First, the market results need to be available to a potential power plant operator. Second, the volume and power requirements need to match the available volume of both the wind farm as well as the battery system. Third, the timescales of bidding and settlement of the market needs to correspond to the timescales of the hybrid power plant. Finally, for the accessible markets, a price incentive must be present to obtain a profit from trading on that market. An analysis of the accessibility of the available markets for battery storage systems is presented here.

#### *Inaccessible*

Bilateral trade agreements do not qualify since settled prices and volumes are not publicly available. Furthermore, these agreements are meant to reduce insecurities in real-time pricing of power by

contracting considerable volumes over a large horizon. The opportunities of the battery lie in short-term stability restoration. The spot market (consisting of the Day Ahead and Intraday Market) is partially transparent. The market results of the Day Ahead Market are presented 12 hours before the day of delivery, for the full day. However, the Intraday Market in the Netherlands is structured in such a way that the amount of public information is very limited (Klein Entink, 2017). Since the obligation of the power plant is to the Day Ahead Market, the battery system could serve an assisting role in reducing imbalance of the plant. The TSO TenneT does present the market results of the balancing mechanisms on its transmission services website. The available capacity and corresponding calculated prices are based on a bidding system for all markets. Therefore, the results are available after the timeslot of delivery. This does not directly disqualify the balancing mechanisms as potential markets, however, an intelligent bidding strategy based on historic market results is required. However, the large scale required by the mFRR, as well as the relatively non-transparent nature of this reserve market make it an unlikely source of revenue for battery energy storage solutions. Additionally, TenneT must have full access to the respective reserve at any time of the contracted period.

*Accessible*

The Day Ahead Market and the balancing mechanisms do have individual requirements of volume and power in the minimum bid and step size. For the Dutch Day Ahead, referred to as APX POWER NL DAM, the minimum bid volume and step size is 100 kWh, i.e. 0.1 MWh. The price step size is one Euro cent per MWh, where the minimum and maximum price of any bid is -500 EUR/MWh and 3000 EUR/MWh respectively. Furthermore, the daily auction closes at 12:00 CET on the day preceding the day of delivery. Between 12:00 and 13:50, the purchase and selling orders are matched, and the power price is determined for each hour of the next day. The primary control reserve (FCR) requires a bid size of at least 1 MW, with an equally large bid step size. The contracted reserve capacity must be available for no less than 15 minutes when called upon. After delivery of power, the power unit must restore the contracted capacity within 2 hours. At that time, the contracted power must once again be fully at the disposal of the TSO. This translates in a minimal volume requirement of 0.25 MWh for the FCR market. The second frequency restoration reserve requires a minimum bid of 1 MW, with an equally large minimum step size. It is reported by Movares that the offered capacity must be made available for two

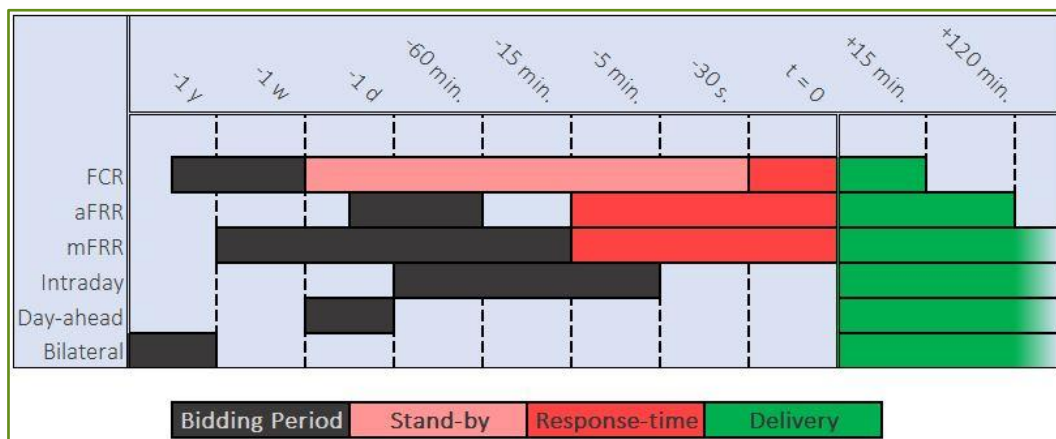


Figure 27: Schedule showing the difference in bidding and delivery of the six identified markets

hours, indicating a minimum volume requirement of 2 MWh (Chang, 2018). None of these requirements disqualify the respective markets for participation of a hybrid power plant.

Figure 27 shows the bidding and delivery schedule of the six identified markets of power trading. The combination of volume and power requirements, availability of market results, and the schedule shown below, make that three markets are accessible for power trading. Primarily, the Day Ahead market fixes the obligation of the hybrid power plant, and it is utilized since it is the main trading platform for power in the Netherlands. Additionally, the primary and secondary frequency reserves (FCR and aFRR) maintained by the TSO are identified as accessible, and possible sources of additional revenue for the plant operator. However, modelling of the FCR market would incorporate too many uncertainties regarding bid acceptance and bid activation to obtain meaningful results.

An example of operation and settlement of a wind farm is presented in Table 3. A power plant operates under obligation to the Day Ahead Market, based on expected production for that day. The true production may deviate from the expected production, and with it, an imbalance occurs. If the imbalance is positive, the excess energy is sold at imbalance prices (Feed In), and if the imbalance is negative, the deficit must be imported at imbalance prices (Feed Out). The obligation to the network is thereby fulfilled, and balance over the plant is maintained. The DAM obligation is settled at the price established by EPEX Netherlands. The imbalance prices are taken from the aFRR balancing mechanism. The variation in both DAM as well as Feed Out and Feed In prices indicate a possible revenue stream for battery energy storage. The separation between generation and supply can lead to increased value of the stored energy.

*Table 3: Calculation example of wind farm power settlement. Data is presented in 15-minute intervals*

Wind farm data [MWh]			Market data [EUR/MWh]			Settlement		
Forecast	Production	Imbalance	DAM	Feed Out	Feed In	DAM	Purchase	Sell
5.5	4.041	-1.459	43.00	46.28	30.28	€236.50	-€67.52	€0.00
5.25	3.408	-1.842	43.00	48.28	48.28	€225.75	-€88.93	€0.00
5	4.426	-0.574	43.00	31.28	31.28	€215.00	-€17.95	€0.00
5	5.009	0.009	43.00	29.55	29.55	€215.00	€0.00	€0.27
5	5.77	0.77	39.28	43.19	43.19	€196.40	€0.00	€33.26
5.25	5.63	0.38	39.28	43.28	33.00	€206.22	€0.00	€12.54
5.25	8.371	3.121	39.28	29.28	29.28	€206.22	€0.00	€91.38
5.5	6.895	1.395	39.28	29.28	29.28	€216.04	€0.00	€40.85
5.5	6.24	0.74	35.75	39.19	39.19	€196.63	€0.00	€29.00
5.75	6.354	0.604	35.75	42.28	42.28	€205.56	€0.00	€25.54
6	4.645	-1.355	35.75	41.78	41.78	€214.50	-€56.61	€0.00
6	5.019	-0.981	35.75	41.28	41.28	€214.50	-€40.50	€0.00
6.25	3.696	-2.554	33.72	41.78	41.78	€210.75	-€106.71	€0.00
6.25	5.054	-1.196	33.72	41.67	41.67	€210.75	-€49.84	€0.00
6.25	5.033	-1.217	33.72	41.28	41.28	€210.75	-€50.24	€0.00
6.25	4.661	-1.589	33.72	38.00	38.00	€210.75	-€60.38	€0.00
						Total: € 3,085.47		

## ***Key Takeaways Chapter 4***

- The Dutch power system is subdivided into four sectors. Generation (power plants), high voltage transmission maintained by the TSO, low voltage distribution managed by DSOs and finally the load
- Generation and load participants are program responsible, but this responsibility can be assigned to a Program Responsible Party
- Aside from bilateral trade agreements, power trading is facilitated by EPEX Netherlands. This platform provides Day Ahead Market and Intraday trading services
- The TSO is responsible for maintaining real time balance on the grid. Fluctuating power sources may result in frequency deviations on the grid, which must be accounted for by frequency restoration services
- Of the six trading mechanisms (bilateral, day ahead, intraday, FCR, aFRR and mFRR), only the Day Ahead Market, FCR and aFRR are accessible to a hybrid power plant and serve as potential sources of revenue
- While the FCR market is deemed accessible for the hybrid power plant, it will not be considered in the modelling and optimization phase due to bid acceptance and activation uncertainties

## Chapter 5: Modelling and Optimization of the Hybrid Power Plant

To find the optimum configuration of the hybrid power plant, a system modelling and optimization routine is proposed. The previous chapters have identified the individual characteristics of the subsystems of a hybrid power plant, this chapter is dedicated to the combined system model and the optimum design configuration of the hybrid power plant. A conceptual model is created to identify the behavior of the hybrid power plant and this, along with the corresponding mathematical formulation, will serve as the basis for the optimization algorithm. Execution of the optimization algorithm is discussed, and the results are presented and analyzed.

## Modelling of the hybrid power plant

### Conceptual model

The conceptual model of the hybrid power plant is formulated to define and categorize the individual subsystems, as well as their relation to one another. The first distinction to be made is between the technical and economical side of the system. Similar to the market separation described by de Vries, as discussed in chapter 4 (de Vries, 2018), the technical side envelops of the physical subsystems: the wind farm, battery system and net connection cable. The economical side of the system consists of the relevant power markets, as identified in chapter 4. These concepts are the basis of all further modelling and optimization. All markets and subsystems have their own characteristics, but it is essential to consider them in the total picture, and their relation to one another.

On the technical side of the system, the main element is the wind farm, controlled by the operator. The hybrid power plant has the addition of a battery energy storage system, as opposed to a conventional wind farm. These two systems are connected to the economical side by the net connection cable. Three modes of energy transfer are present within the technical side of the system: power production by the wind farm, discharging of the battery, and charging of the battery. The economical side of the system is defined by the accessible markets to the hybrid power plant. Most significantly, the Day Ahead Market (DAM) establishes the obligation of the wind farm through the bidding process described in chapter 4. When the production of the wind farm is insufficient to fulfill the obligation, the imbalance is corrected by the battery system or settled against imbalance prices defined by the aFRR market. There is no actual energy transfer on this economical side, since the net connection cable links the hybrid power plant with the national high voltage net operated by the TSO. The economical side only deals with the obligation of the hybrid power plant to the grid, and the settlement of energy against the respective prices. An illustration: if the obligation at a given interval is equal to 5 MWh, and the true production is 4 MWh at a time that the battery is empty, the 4 MWh are transported to the grid as usual. However, the imbalance that occurs must be settled at prices defined by the aFRR market. Figure 28 shows the individual subsystems and their relation to one another. Energy balance on the net connection cable, presented in the figure by the vertical line, is the basis for the mathematic formulation of the model, as well as for the optimization algorithm to be discussed later on in this chapter. The model is expanded by unambiguous assumptions and the constraints of the individual subsystems. The assumptions are numbered, and the constraints indicated by lowercase letters for future reference.

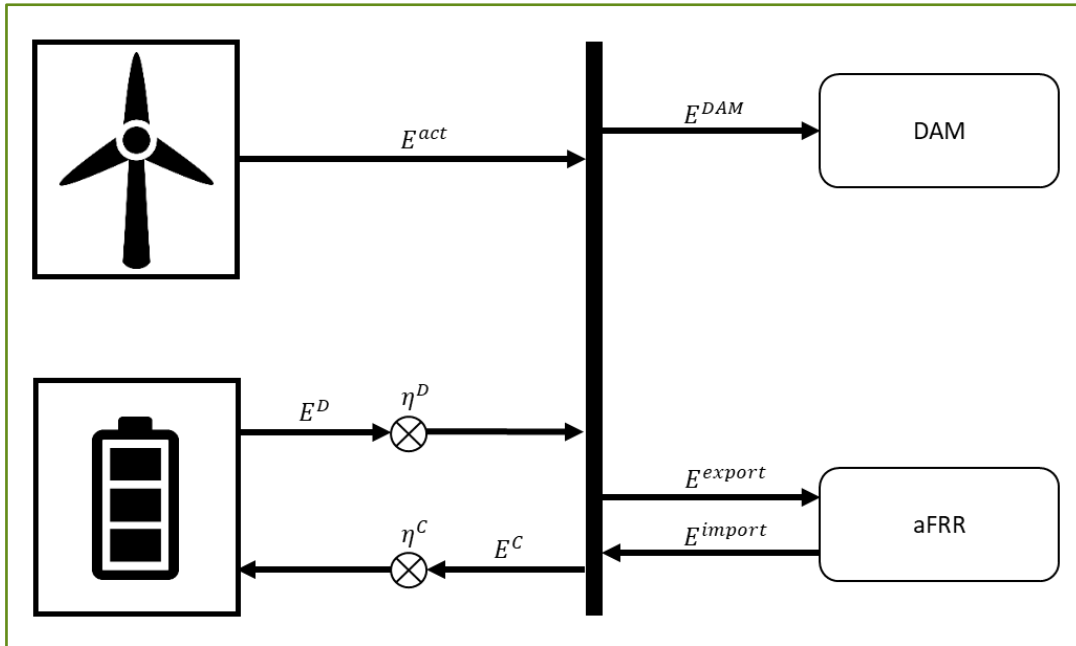


Figure 28: Graphical representation of the hybrid power plant, with the physical layer on the left and the economical layer on the right

## Assumptions

### 1. The hybrid power plant is balance responsible

It is assumed that the hybrid power plant is a balance responsible party on its own. In a more realistic scenario, the mismatch between bid and true production could be partially settled within the portfolio of the designated PRP. However, this study focusses on the additional value of a battery system as a balancing mechanism for a wind farm, and the ultimate balance within the plant is aimed for. Because of this assumption, the mismatch between market obligation and true production within the hybrid power plant may be relatively large. This is the case when no production is expected, a bid is performed accordingly, and the maximum power is achieved for the duration of the bid (one hour for the Day Ahead Market). Therefore, it is expected that the minimum optimal battery capacity for a wind farm approaches the maximum attainable energy of the wind farm in one hour. An additional effect of this assumption is that the settlement of imbalance may result in large costs and benefits (depending on the direction of imbalance). It is assured that the plants obligation to the Day Ahead Market is assured with the assistance of the battery and settlement on the aFRR imbalance market.

### 2. Battery assists wind power production

The battery system is intended to assist the hybrid power plant in maintaining balance between generation and obligation. Therefore, it is assumed that the battery is charged primarily with energy generated by the wind farm. The associated constraint is that the charge value may not exceed the wind power production value. Optimization of the charge/discharge strategy may employ imbalance trading directly with the battery, but in the case of battery capacity optimization, importing excess net power can lead to excessive battery capacity requirements and oversaturation of the national imbalance market.

### *3. Net connection capacity*

The hybrid power plant is designed based on an existing wind farm. It is assumed that the net connection capacity is equal to the wind farm power capacity plus a 30% margin. Furthermore, it is assumed that the net connection cable is already available and poses no extra investment during the development of a hybrid power plant as proposed in this study.

### *4. Battery aging*

Aging of battery cells is dominated by two mechanisms: calendar aging and cycle aging. Both are modelled to occur linearly in time and number of performed cycles, respectively. Calendar aging is taken as a factor in the determination of the system costs by spreading the investment cost out over the total lifetime of the battery system. The cycle aging is predominantly determined by the capacity fade of the battery. A battery system is considered to be fully degraded when the available capacity drops below 80% of the original capacity (Buchmann, 2018). Cycling age is a given parameter for a specific technology and ranges from 500 to approximately 20.000 equivalent charge/discharge cycles depending on the technology and scenario considered (IRENA, 2017), see Table 7). For each full charge, the available battery capacity (volume in MWh) is reduced by the reciprocal of the cycling life multiplied by 20% of the original capacity. For example, a 10 MWh battery system with a cycling life of 2000 cycles is reduced by 1 kWh in capacity for each full charge/discharge cycle. A full charge discharge cycle consists of 10 MWh of charge, and 10 MWh of discharge. The reduction of the battery capacity as a result of cycling is referred to as 'capacity fade'.

### *5. Battery power vs. volumetric capacity*

It is assumed that the maximum C-rate of the battery system (as defined in chapter 3) is equal to one. In other words, the maximum charge and discharge rate is the rate it takes to charge or discharge the battery in one hour. A C-rate of one for a 10 MWh battery system corresponds to a 10 MW power rating. Since the optimal battery size is likely to be of the same scale as the wind farm capacity, it is desirable that the battery has similar power capabilities. It is therefore expected that the optimal battery size will be of the same order of magnitude as the maximum hourly production of the wind farm. Additionally, it is reported that higher charge or discharge ratings can lead to faster degradation of battery cells due to induced stresses within the anode and cathode materials. Naturally, charging and discharging rates corresponding to a C-rate of less than one are possible.

### *6. Capital and operational expenditures*

The cost of installation and operation of the battery system is expressed in capital and operational expenditures, CAPEX and OPEX respectively. Aside from the installation costs of a battery system, as presented in the cost breakdown in chapter 3, the cost of operation must be considered. These costs include efficiency losses, maintenance, repairs and battery cell replacements. For a battery system with a 12-year lifetime, the total operational costs range from 11% to 33% of the capital expenditures (Rahmann, 2017). It is therefore assumed that the total OPEX of the battery system in the hybrid power plant is 30% of the CAPEX. It is furthermore assumed that the OPEX is operation dependent, an installed system that is not operational (no charging or discharging) has no operating expenses. The OPEX therefore scales with the equivalent full charge/discharge cycles, as indicated by equation 5.13.

### 7. Perfect foresight is applied regarding market results

For battery capacity optimization purposes, it is assumed in this battery capacity optimization phase that the hybrid power plant operates on perfect foresight on the available markets. This means that all market price series are available beforehand, and the optimization algorithm will search for a global optimum. As a result, the maximum attainable revenue is determined. Additionally, it is assumed that the imbalance prices presented on the transmission website of TenneT are representative for aFRR trading.

### 8. Reference scenario

To properly analyze the behavior of the hybrid power plant, a reference scenario must be defined. The proposed scenario corresponds with the calculation example in Table 3 in chapter 4, and it defines the energy trading of a wind farm without battery storage to the accessible markets. The subsequent steps of a power plant in this reference scenario are given by items 1 to 5. Since the profitability of the hybrid power plant is a key factor in determining its feasibility, it is essential to have this reference scenario to compare the results to.

1. A bid ( $\underline{E}^{DAM}$ ) is submitted to the Day Ahead Market at 12.00
2. At a given moment, when true production is lower than the bid volume, energy is purchased from the imbalance market at import price  $MP_t^{import}$
3. When the production is higher than the bid volume, energy is sold to the imbalance market at export price  $MP_t^{export}$
4. The relevant volumes are: satisfied DAM volume  $\underline{E}^{DAM}$ , exported imbalance volume  $\underline{E}^{export}$ , and imported imbalance volume  $\underline{E}^{import}$
5. The total revenue is calculated by equation 5.1

$$R_{ref} = \sum (E_t^{DAM} MP_t^{DAM} + E_t^{export} MP_t^{export} - E_t^{import} MP_t^{import}) \quad (5.1)$$

## Constraints

### a. Energy balance

The energy flows on the net connection cable must be balanced at all times, no energy is lost. The volumes of energy produced by the power plant, the energy discharged from the battery (reduced by the discharge efficiency) and the energy imported from the aFRR imbalance market must equal the energy charged to the battery, sold to the DAM market and the aFRR imbalance market at all times.

### b. Net connection capacity

The net output of the plant, which is determined by the power sold to the available markets, may never exceed the net connection capacity. An example: if the net connection capacity is 10 MW, the wind farm produces 9 MW, and the battery discharges due to a favorable price incentive of the aFRR market, the maximum discharge power is 1 MW. On the contrary, if there is a price incentive to import power from the aFRR market to charge the battery, this power must be subtracted from the produced power over the connection cable.

### *c. Definition of the battery level*

The available capacity of the battery at any given moment is referred to as the battery level, presented in MWh. The level changes over time subject to charging and discharging of the battery. The difference between the battery level between two subsequent time steps is equal to the difference between charge and discharge at that time. Several constraints apply, the most evident of which is the fact that the battery level may not exceed the battery capacity in MWh. Other constraints regarding the battery level are the lower and upper charging limits prescribed by a DOD limit for safe and sustainable operation, typically between 70 to 90% depending on the technology. Charging and discharging may never lead to exceedance of these limits (further elaborated in constraint d). Careful attention to the battery charge and discharge efficiency is required. Figure 28 indicates at what point the respective energy flows must be multiplied with their efficiencies. The battery level difference due to discharge must be multiplied with the discharge efficiency before adding it to the energy balance. Energy dedicated to charging the battery as noted in the energy balance must be multiplied with the charge efficiency before adding it to the battery level.

### *d. Upper and lower charging limits*

As described in chapter 3, the depth of discharge is one of the crucial control parameters in the operation of a battery system. Certain limits are established for safe and sustainable operation. This leads to limitations on the maximum and minimum charge level. For a given maximum depth of discharge in percent, these limits are defined by half of the remaining capacity in percent. For instance, the lower charging limit for a system with a maximum DOD of 80% is equal to 10% of the available capacity. The battery level (state of charge) may not be lower than 10% or higher than 90%.

### *e. Maximum charge and discharge rate*

The charging and discharging rate may not exceed the power rating of the battery. The model is designed in terms of energy volume, and so have the charge and discharge variables. The maximum charge and discharge rate are therefore also defined in a volumetric component, which is determined by multiplying the power rating by the primary time unit (PTU). For example, a battery system with a power rating of 10 MW is limited to charging or discharging 2.5 MWh per 15 minutes. Exceeding these charge and discharge limits will lead to accelerated degradation of the battery system.

## Mathematical model

The mathematical model is meant to describe the behavior of the subsystems, as well as the relation between them in comprehensible equations. This mathematical model combines the concepts, constraints and assumptions that have been described thus far. A nomenclature is presented in Table 4 and Table 5, where a provisional division is made between parameters and variables in the model. In the optimization stage of this study, the time dependent timeseries  $\underline{E}^{DAM}$ ,  $\underline{E}^{act}$ ,  $\underline{MP}^{DAM}$ ,  $\underline{MP}^{export}$  and  $\underline{MP}^{import}$  are presented as parameters since these series serve as the input to the algorithm. Other quantities such as battery size, CAPEX and OPEX are presented as variables since these depend on the size of the battery and the equivalent full charge/discharge cycles. Since the economical side of the model is governed by market prices presented in a price per volume of energy, a discrete model is

presented on the basis of 15-minute primary time units (PTU's) in which energy is produced and sold to the respective markets.

*Table 4: Hybrid power plant model parameters*

Parameter	Unit	Description
<b><math>BC</math></b>	$\left[\frac{EUR}{MWh}\right]$	Battery installation cost
<b><math>CL</math></b>	$[-]$	Battery cycling life in number of full charge/discharge cycles
<b><math>DOD</math></b>	$[\%]$	Maximum allowable depth of discharge
<b><math>E_t^{act}</math></b>	$[MWh]$	True production of the wind farm at PTU $t \in \{1,2, \dots T\}$
<b><math>E_t^{DAM}</math></b>	$[MWh]$	DAM obligation based on bid at PTU $t \in \{1,2, \dots T\}$
<b><math>\eta^C</math></b>	$[\%]$	Charge efficiency
<b><math>\eta^D</math></b>	$[\%]$	Discharge efficiency
<b><math>LT</math></b>	$[-]$	Battery lifetime expressed in number of PTU's
<b><math>MP_t^{DAM}</math></b>	$\left[\frac{EUR}{MWh}\right]$	Day Ahead Market price at PTU $t \in \{1,2, \dots T\}$
<b><math>MP_t^{export}</math></b>	$\left[\frac{EUR}{MWh}\right]$	Export price at PTU $t \in \{1,2, \dots T\}$
<b><math>MP_t^{import}</math></b>	$\left[\frac{EUR}{MWh}\right]$	Import price at PTU $t \in \{1,2, \dots T\}$
<b><math>NC</math></b>	$[MWh]$	Net connection capacity expressed in maximum allowable PTU volume
<b><math>R_{OC}</math></b>	$[-]$	Ratio of OPEX to CAPEX
<b><math>T</math></b>	$[-]$	Number of PTU's in simulation
<b><math>TF</math></b>	$[-]$	Total fraction of battery capacity faded at end-of-life

Table 5: Hybrid power plant model variables

Variable	Unit	Description
$BL_t$	[MWh]	Battery level at PTU $t \in \{1,2, \dots T\}$
$BS$	[MWh]	Battery size (volume capacity)
$CAPEX$	[EUR]	Capital expenditures
$CF_t$	[MWh]	Capacity fade due to cycling at PTU $t \in \{1,2, \dots T\}$
$E_t^C$	[MWh]	Positive charge volume at PTU $t \in \{1,2, \dots T\}$
$E_t^D$	[MWh]	Positive discharge volume at PTU $t \in \{1,2, \dots T\}$
$E_t^{export}$	[MWh]	Positive volume sold to imbalance market at PTU $t \in \{1,2, \dots T\}$
$E_t^{import}$	[MWh]	Positive volume purchased from imbalance market at PTU $t \in \{1,2, \dots T\}$
$OPEX$	[EUR]	Operational expenditures
$t$	[–]	Time expressed in number of PTU's passed
$TC_t$	[MWh]	Total volume previously charged at PTU $t \in \{1,2, \dots T\}$

#### Constraints

The behavior of the hybrid power plant is described by the energy balance over the net connection cable and the constraints of the individual systems. These constraints must be satisfied at all times during the simulation. The energy balance presented in 5.2 states that produced, discharged, and imported (from the imbalance market) energy must equal the energy sold to the DAM and the imbalance market, and the energy charged to the battery. Moreover, the net energy leaving the plant must not exceed the net connection capacity as noted in equation 5.3. Equation 5.4 states that, in case of importing energy to charge the battery, the imported volume cannot exceed the net connection capacity.

$$E_t^{act} + \eta^D E_t^D + E_t^{import} = E_t^{DAM} + E_t^{export} + E_t^C, \forall t \in \{1,2, \dots T\} \quad (5.2)$$

$$E_t^{DAM} + E_t^{export} \leq NC, \forall t \in \{1,2, \dots T\} \quad (5.3)$$

$$E_t^{import} \leq NC, \forall t \in \{1,2, \dots T\} \quad (5.4)$$

The definition of the battery level is given in equation 5.5, relating the battery level in a previous PTU to the current state based on the current charge and discharge volumes. The battery system is subject to charging and discharging constraints. The battery cannot be discharged more than the lower charging level, defined by the maximum DOD, dictates equation 5.6. Additionally, the battery level may not exceed the upper charging limit determined by the allowable depth of discharge (equation 5.7). Furthermore, battery aging is considered: for every full charge cycle, the maximum battery level is reduced with the variable capacity fade (equation 5.8). This capacity fade at any given time is determined by calculating the cumulative charge ('total charge', equation 5.9) the system has gone through up to that moment and scaled with the number of PTU's in the simulation. In other words, the maximum capacity fade for a battery with a 10-year lifetime for a simulation of one year is 1/10<sup>th</sup> of the total capacity fade during the lifetime.

$$BL_t = BL_{t-1} + \eta^c E_t^c - E_t^d, \forall t \in \{1, 2, \dots, T\} \quad (5.5)$$

$$BL_t \geq \left(0.5 - \frac{DOD}{2}\right) BS, \forall t \in \{1, 2, \dots, T\} \quad (5.6)$$

$$BL_t \leq \left(0.5 + \frac{DOD}{2}\right) BS - CF_t, \forall t \in \{1, 2, \dots, T\} \quad (5.7)$$

$$CF_t = \frac{TF \cdot T}{CL \cdot LT} TC_t, \forall t \in \{1, 2, \dots, T\} \quad (5.8)$$

$$TC_t = \sum_{t_1=1}^t E_{t_1}^c, \forall t \in \{1, 2, \dots, T\} \quad (5.9)$$

Assumption 5 states that the maximum C-rate of the battery is equal to 1. In other words, the battery system can be fully charged or discharged in one hour. The resulting constraints are that the charging volume in a PTU cannot exceed a quarter of the battery size, since the PTU size is a quarter of an hour. Finally, as per assumption 2, the battery assists wind power production, and the charge variable can therefore not exceed the wind power production, presented by equation 5.12.

$$E_t^c \leq \frac{BS}{4}, \forall t \in \{1, 2, \dots, T\} \quad (5.10)$$

$$E_t^d \leq \frac{BS}{4}, \forall t \in \{1, 2, \dots, T\} \quad (5.11)$$

$$E_t^c \leq E_t^{act} \forall t \in \{1, 2, \dots, T\} \quad (5.12)$$

The relationship between the assumptions, constraints and equations of the model are presented in Table 6.

Table 6: Relationship between equations, assumptions and constraints

Equation	Assumption	Constraint
5.2	1	a
5.3	3	b
5.4	3	b
5.5		c
5.6		d
5.7	4	d
5.8	4	
5.9	4	
5.10	5	e
5.11	5	e
5.12	2	

## Linear optimization initialization

### Objective function

The objective of the optimization model is to maximize the revenue created by trading in volumes of energy. The revenue generating volumes (imbalance settlement) are considered in the objective function along with their respective market prices. Trading on the Day Ahead Market is irrelevant in the formulation of the objective function, since it is assured that the submitted bid is satisfied. The capital expenditures (CAPEX) are scaled with the simulation length with respect to the calendar lifetime. The operational expenditures (OPEX) are scaled with the equivalent full charge cycles with respect to the number of lifetime full cycles. CAPEX is a function of the battery capacity, whereas the OPEX is a function of the total volume charged to the battery.

$$CAPEX(BS) = \left( \frac{BC \cdot T}{LT} \right) BS \quad (5.13)$$

$$OPEX(E^C) = \frac{R_{oc} BC}{CL} \sum_{t=1}^T E_t^C \quad (5.14)$$

$$\text{maximize } \sum_{t=1}^T [MP_t^{\text{export}} E_t^{\text{export}} - MP_t^{\text{import}} E_t^{\text{import}}] - CAPEX(BS) - OPEX(E^C) \quad (5.15)$$

While the objective function maximizes the profit obtained from energy imbalance trading, the resulting value is not the revenue. Since it is assured that the DAM bid is satisfied, the volumes sold to the Day Ahead Market do not need to be optimized. The revenue is the sum of all energy streams sold to both the Day Ahead Market as well as the imbalance market and includes the scaled values for the CAPEX and OPEX, as given by equation 5.16.

$$\text{Revenue} = \sum_{t=1}^T [MP_t^{\text{DAM}} E_t^{\text{DAM}} + MP_t^{\text{export}} E_t^{\text{export}} - MP_t^{\text{import}} E_t^{\text{import}}] - CAPEX(BS) - OPEX(E^C) \quad (5.16)$$

### Decision and assisting variables

In this design phase of the study, the objective is to find the optimal configuration of the hybrid power plant. It is assumed that the wind farm data is a given, therefore, the configuration of the hybrid power plant is determined by the optimal battery capacity. The main decision variable is therefore the battery

capacity, an optimum value must be found. Additionally, the objective function is governed by the energy volumes sold to the respective markets, and the energy volumes charged to the battery. Energy volumes sold to their respective markets determine the cashflows of the hybrid power plant, whereas the energy volume charged to the battery determines battery degradation and the operational cost. Since an optimum battery capacity is judged by the profitability of the configuration, the cashflow generating energy volumes and battery charge volume are additional decision variables that are to be optimized by the algorithm. Other variables, such as the battery level and total capacity fade at a given time are considered assisting variables. These are derived from the decision variables and their influence on the profitability of a configuration is indirect.

### Wind power production data

The model of the hybrid power plant has now been described in full. Execution of the algorithm requires input data, which is provided in the form of production data and corresponding price series. All of this data is provided by a previous project executed by Ecofys, known as Wind Prediction Services (WPS) for an onshore wind farm with a power capacity of 60 MW. The dataset includes the DAM bid generated by Wind Prediction Services, actual production and the corresponding price levels for each PTU in a year, for the years 2009 up to and including 2015. The price series are validated against data provided by ENTSO-E. Since the data resolution is on PTU basis, a dataset for one year contains 35040 datapoints (35136 datapoints for the leap year 2012).

### Battery parameters

The efficiency in charging and discharging the battery has been mentioned in the introduction of the conceptual model. Additional limitations and constraints on operation of battery systems are identified. First, the depth-of-discharge of a battery has significant impact on the battery life. Therefore, it should be kept within acceptable limits. Second, aging mechanisms of the battery lead to degradation. The calendar lifetime of a battery (in years), as well as the cycle life of the battery (in full charge/discharge cycles) limit the operation of the system. An extensive study by the International Renewable Energy

*Table 7: Battery characteristics for 2016 and 2030, identified for three possible scenarios (IRENA, 2017)*

		Calendar life (years)			Cycle life (eq. full cycles)		
Technology	Year	worst	reference	best	worst	reference	best
LFP	2016	5	<b>12</b>	20	1000	<b>2500</b>	10000
	2030	8	18	31	1910	4774	19097
NMC	2016	5	<b>12</b>	20	500	<b>2000</b>	4000
	2030	8	18	31	955	3819	7639

*Table 8: (Continuation of Table 7)*

		Max DOD (%)			Energy installation cost (USD/kWh)			Round trip efficiency (%)
Technology	Year	worst	reference	best	worst	reference	best	reference
LFP	2016	84	<b>90</b>	100	5	<b>12</b>	20	<b>92</b>
	2030	84	90	100	8	18	31	94
NMC	2016	84	<b>90</b>	100	5	<b>12</b>	20	<b>95</b>
	2030	84	90	100	8	18	31	97

Agency (IRENA) has identified the characteristics of a wide range of energy storage methods ranging from pumped hydro storage to vanadium redox flow batteries. The previously identified lithium-ion battery technologies (LFP and NMC) are also represented in the report. Table 7 and Table 8 present the findings of IRENA. Some additional characteristics are mentioned in the report such as energy and power densities and self-discharge of the battery. However, energy density and power density do not influence the applicability of a certain technology since no spatial constraints are assumed. Furthermore, a self-discharge rate of 0.1% per day in the reference scenario is deemed negligibly small, especially for the timescales of operation considered. The values used in the battery capacity optimization are presented in bold in Table 7 and Table 8, corresponding to the '2016/reference' scenario in the IRENA study. The charge and discharge efficiencies are taken to be the square root of the round trip efficiency.

## Simulation and results

The optimization sequence is performed in MATLAB, a MathWorks desktop programming environment (MathWorks, 2018). MATLAB has the advantage of an own integrated development environment, but more importantly, a large number of packages and toolkits, including the Optimization Toolbox. The MATLAB Optimization Toolbox is used in this study to find the optimum battery capacity. The objective is two-fold: to minimize the imbalance between market obligation and production, and to maximize the profit of the hybrid power plant. The minimization of the imbalance between market obligation and true production of the plant is guaranteed with *assumption 1*, and *constraint a* (the plant is balance responsible). The mismatch between obligation and true production is accounted for at all times by a combination of the battery system and the secondary frequency control reserve (aFRR). Maximization of the profit returned by the hybrid power plant within the boundaries of operation is therefore the main optimization criterium, and the objective function is established accordingly.

The optimization sequence is performed for the seven individual years for which the production data was available. Simulation of more than one year leads to excessive computational times, and in extreme cases even to failure to execute. The relevant outputs of the algorithm are the optimal battery capacity in MWh, the revenue obtained by trading with the battery, the corresponding CAPEX and OPEX, and a profitability indicator. The profitability indicator is a performance measure that relates the profit of the

*Table 9: Terminology used in results*

<b>Term</b>	<b>Description</b>
<b>Battery capacity</b>	Energy rating of the batter expressed in MWh
<b>Revenue</b>	All earnings from trading energy
<b>Profit</b>	Revenue minus installation and operational costs
<b>Reference revenue</b>	All earnings from trading energy in the reference scenario of trading without a battery (assumption 8)
<b>Profitability</b>	Difference between profit and reference revenue, expressed in a percentage of the reference revenue

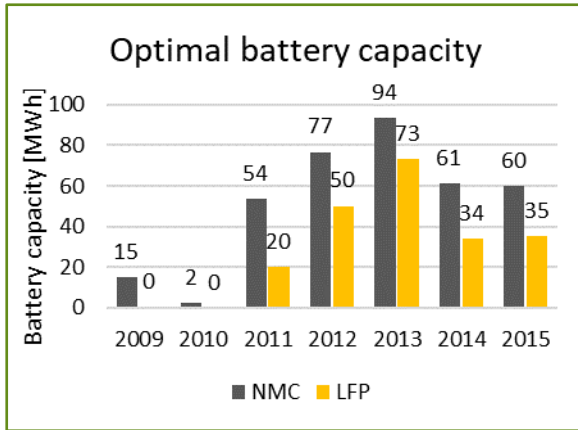


Figure 29: Optimal battery capacity for seven individual years

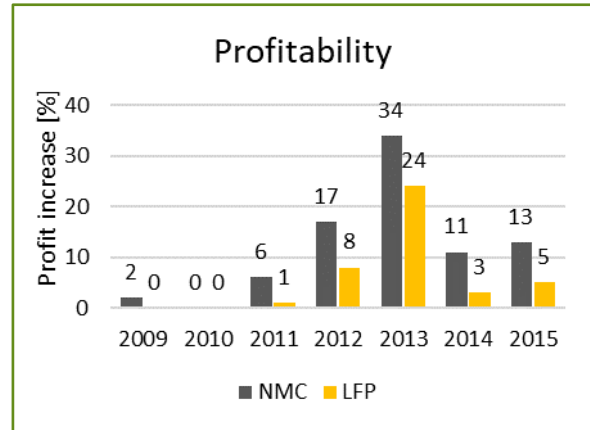


Figure 30: Profitability for optimal battery capacity

hybrid power plant to the reference scenario (assumption 8: regular wind farm trade, no battery). The terms used in the presentation of the results are described in Table 9.

## Results

Execution of the algorithm leads to the results presented in Figure 29 and Figure 30. The aim of the algorithm is to find the optimal battery capacity (or battery capacity) in MWh for the given wind farm with power capacity of 60 MW. Therefore, the optimal battery capacity is the first outcome to be considered. Figure 29 shows the optimal battery capacity for both nickel manganese cobalt oxide and iron phosphate lithium-ion battery technologies. The optimal battery capacity for LFP is significantly smaller for each individual year considered, by an average margin of 40% compared to NMC. The optimal battery capacity ranges from 0 to 73 MWh for LFP, and from 2 to 94 MWh for NMC. It will be shown that the main cause of the large deviation between years is the variability of the imbalance price throughout each year. The corresponding obtained profitability is presented in Figure 30. As with the battery capacity, the profitability obtained by the NMC technology is higher than for LFP in all cases.

A closer look at the obtained revenues is presented in Figure 31 and Figure 32. For each of the individual years, for both technologies, the revenue of the hybrid power plant is higher than the revenue of the reference scenario. However, the significant costs of the battery technologies reduce the profit of the configuration. In the years 2009 and 2010, the optimal battery size is relatively small or even zero,

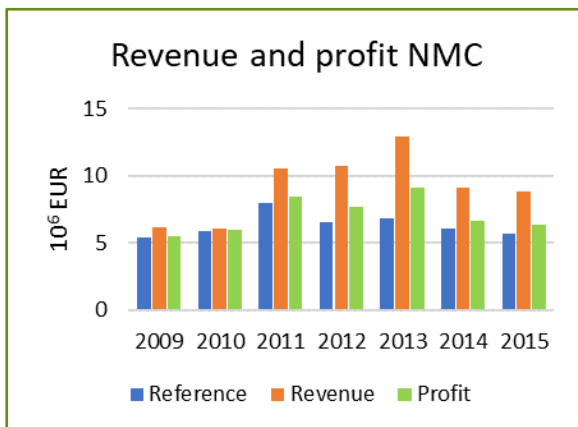


Figure 31: Comparison of revenue and profit for optimized NMC battery

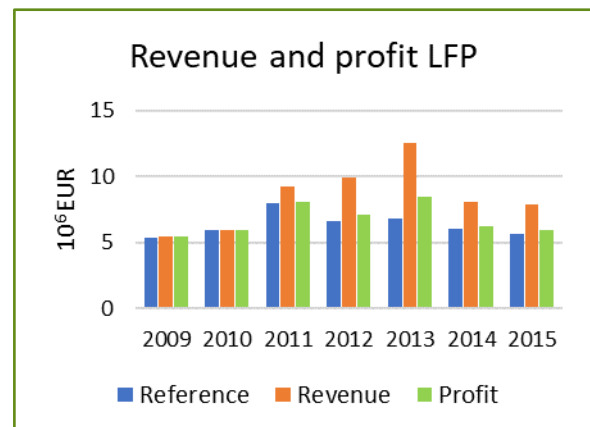


Figure 32: Comparison of revenue and profit for optimized LFP battery

and therefore there is a minimal difference between the trading revenue and the reduced revenue. All in all, of the 14 inspected cases (seven years, two battery technologies), only three resulted in a profitability of zero while eight cases resulted in a profitability of more than 5%.

Finally, the return on investment (ROI) is calculated for each simulated case. The ROI is the ratio between the profit and the battery installation cost (CAPEX). It is an indication of how profitable an investment is. Table 10 shows the ROI values for both NMC as well as LFP simulations of all available years. The 2009/LFP simulation indicates an ROI of 39%, while the battery capacity (Figure 29) and profitability (Figure 30) are equal to 0 MWh and 0% respectively (these values are rounded to the nearest integer). The reason for such a high ROI stems from the fact that the 2009/LFP profit is non-zero, and the required battery capacity is very small, as is the corresponding CAPEX. The 2010/LFP simulation indicates a 0% ROI since the battery capacity is truly zero. The other ROI values range from 12% to 81%, the latter being the most extreme case in the profitable year of 2013. It is therefore concluded that the investment required for the battery system can make a hybrid power plant highly profitable when operated at perfect foresight.

*Table 10: Return on investment optimized hybrid power plant*

Year	ROI [%]	
	NMC	LFP
<b>2009</b>	24	39
<b>2010</b>	24	0
<b>2011</b>	29	13
<b>2012</b>	47	26
<b>2013</b>	81	53
<b>2014</b>	34	12
<b>2015</b>	39	20

Since it is expected that the hybrid power plant will be operational for the full lifetime of the battery, a simulation of a single year does not adequately represent the optimal design conditions. Additional simulations are therefore performed for a length of four years (simulations of more than four years require more computational power than available). Three ranges are extracted from the available data: 2010 – 2013, 2011 – 2014 and 2012 – 2015. Within the previously established range, the optimization algorithm is executed for fixed battery capacities, for the better performing NMC technology. As a result, the simulation time is significantly lower than when the battery capacity is one of the optimization variables, and a trend emerges regarding the profitability as a function of the battery capacity. Figure 33 shows the data points for the three simulated ranges, connected by a parabolic trendline for illustrative purposes. Up to a certain point, a higher capacity battery results in a higher profitability. However, as the battery capacity increases further, the capital and operational costs of the battery system outweigh the potential revenue increase, as is the case for a 100 MWh battery in the 2012 – 2015 range (no revenue increase is found). The optimum battery capacity range for a 60 MW wind farm is, based on Figure 33, 60 to 80 MWh.

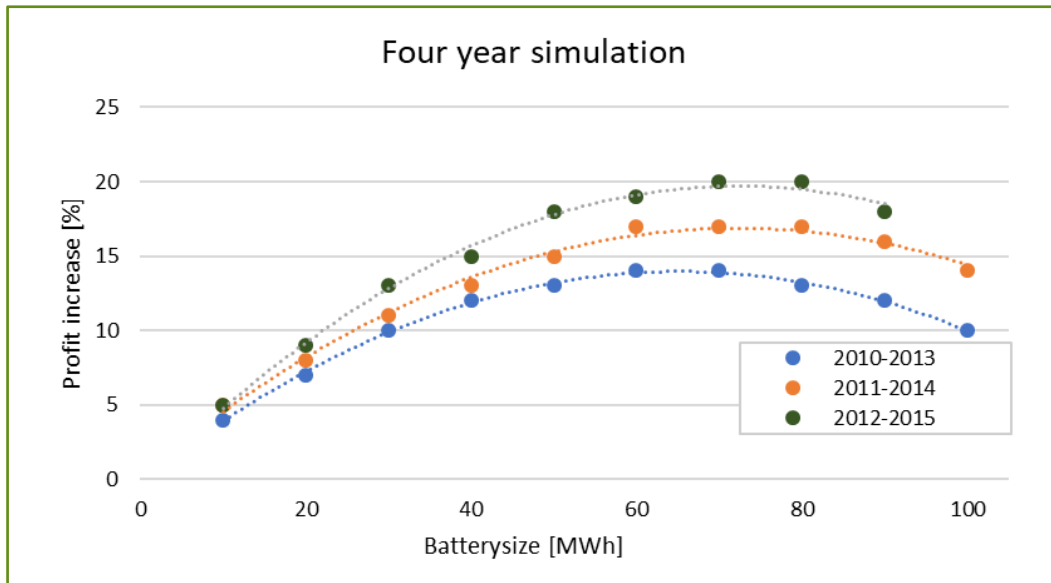


Figure 33: Optimal battery capacity (NMC) obtained by simulation of four subsequent years

### Analysis

The presented model is validated by means of increasing the battery installation cost parameter by a factor of 10. At these installation (and indirectly operational) costs, the optimization algorithm must return an optimal battery capacity of zero. The obtained revenue is then compared to the reference trading scenario, returning a deviation of less than 1% in all simulated years. The error stems from differences in market price between importing and exporting imbalance. A sensitivity analysis regarding the 60 MW wind farm as input is performed. Since the underlying model of the optimization algorithm is completely linear, the optimal battery capacity must scale linearly with the power capacity of the wind farm. Based on single-year simulations for 20, 40, 60 and 80 MW wind farms, this hypothesis is fully confirmed. Furthermore, the assumption of perfect foresight is tested as well, not to determine the validity of perfect foresight, but to indicate the relevance of accurate market price approximation. It is shown that an increased error over the market prices leads to inaccurate revenue forecasting and loss of profitability. The validation and sensitivity analyses are presented in Appendix 1 of this report.

Since the initial simulations are performed on a single-year basis, variation between the individual years is to be expected. However, the severity of the variations leads to serious consideration. Finding the root cause is not only relevant for clarifying the differences in results between the simulations, it also leads to better understanding of the underlying mechanisms behind the revenue generation of the hybrid power plant.

First, potential causes of profitability variation between the years are identified. DAM trading is applied for both the reference scenario as well as for the hybrid power plant. Therefore, the revenue increase of the hybrid power plant is mainly determined by imbalance settlement, and not by the total produced energy. The *level of imbalance* is the first potential cause of the profitability variation. Stored energy in the battery may increase in value by settlement at elevated imbalance prices. The imbalance market price characteristics determine the value of stored energy. Both *average imbalance settlement prices* as well as *imbalance settlement price variation* potentially lead to the severe variation in profitability between the years. These causes are presented in Table 11 with their corresponding values. At first

Table 11: Potential underlying causes of profitability

Year	Profit increase [%]	Average imbalance [MWh]	Average imbalance price [EUR/MWh]	Imbalance price standard deviation [EUR/MWh]
2009	2	0.246	40.63	51.24
2010	0	-0.589	44.45	43.55
2011	6	0.204	49.82	55.53
2012	17	-0.320	50.34	67.34
2013	34	0.061	55.51	83.13
2014	11	-0.610	42.10	55.70
2015	13	-0.307	43.86	66.96

glance, it becomes apparent that the well performing years 2012 and 2013 have the largest imbalance price standard deviation, whereas 2009 and 2010 have significantly lower values, corresponding to their minimal profitability. The same is true, in a lesser extent, of the average imbalance price. The average imbalance over all PTU's seems to be completely random with regards to the profitability of the individual years.

By means of correlation analysis, the three potential causes of profitability are investigated. Eventually, the root cause of revenue increase compared to the reference scenario is shown to be the variation in the imbalance price. The standard deviation of the imbalance price series strongly correlates to the revenue increase of each individual year. Additionally, as the imbalance market allows for profitable trading of energy volumes, favorable imbalance price fluctuations leads to larger optimal battery capacity. The correlations are illustrated in Figure 34 and Figure 35. The profitability, expressed in terms of revenue increase compared to the base scenario, has a linear correlation of nearly 0.95 with the standard deviation of the imbalance price. A correlation of 0.81 is found for the optimal battery capacity. A first conclusion is therefore that the variation in the imbalance price is the crucial parameter in determining the profitability of the hybrid power plant.

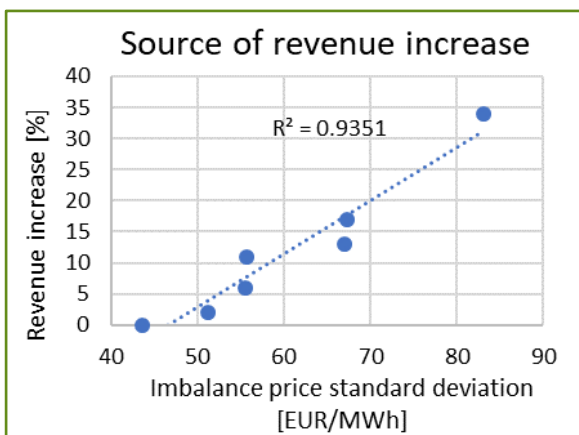


Figure 34: Correlation between imbalance price standard deviation and profitability (NMC)

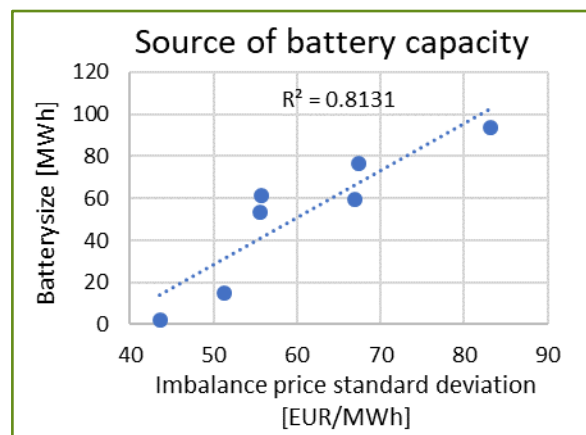


Figure 35: Correlation between imbalance price standard deviation and optimal battery capacity (NMC)

## ***Key Takeaways Chapter 5***

- Conceptual modelling of the hybrid power plant describes both a technical and an economical side. The technical side contains the wind farm, the battery system and the net connection, the economical side contains the relevant energy markets
- The mathematical formulation of the model is based on the energy balance over the net connection cable and elaborated by constraints of the individual subsystems
- The optimization algorithm is built upon the mathematical formulation of the model. The objective function aims to maximize revenue by energy trading, while considering the CAPEX and OPEX of the battery system
- Optimization results show that hybrid power plant energy trading allows for trading revenue increase in nearly all simulated years.
- Lithium-ion nickel manganese cobalt oxide battery technology performs better than lithium-ion iron phosphate in all instances in terms of profitability of the hybrid power plant
- The optimal battery capacity for a wind farm with a 60 MW power capacity is in the range of 60 – 80 MWh
- Imbalance price variation is the driving force behind the profitability of the hybrid power plant. A large standard deviation results in an increased revenue potential

## Chapter 6: Development of an Operational Tool for the Hybrid Power Plant

Up to this point, the data used for optimization was based on the assumption of perfect foresight. For the purpose of determining the optimal design configuration, perfect foresight is an adequate way of providing the necessary input data. However, the next phase of the study deals with the development of an operational tool to determine the charge/discharge and settlement strategy based on real-time data. This requires a different approach to the structure of the optimization model as well as the required input data. Model Predictive Control (MPC) is used to optimize the strategy up to a certain horizon based on the most recent available data.

### Introduction to Model Predictive Control

Model Predictive Control is an advanced control technique for multivariable control problems. MPC has been around since the 1980's, used for the operation and control of chemical plants and oil refineries. More recently, it has also been used in power system balancing models. MPC is a feedback control algorithm that uses a model to make predictions about future outputs of the process and is based on solving an optimization algorithm at each step in the process up to a certain horizon. The main advantage of MPC is that it allows the current time step to be optimized while keeping the future timeslots in account. Figure 36 illustrates the difference between basic feedback control and Model Predictive Control. The controller in basic feedback control operates on a setpoint input and the plant behavior. The difference between these two inputs calls for an action, determined by the controller, and fed into the plant as input. While the structure of the MPC feedback loop is similar, the crucial difference is the fact that the MPC controller contains a model of the plant and an optimizer. Based on the same input data as the basic feedback control loop (setpoint and plant behavior), the MPC controller predicts the behavior of the plant for all possible control actions and selects the optimal control action through the optimizer. Where the basic feedback control process instantaneously aims to correct deviations from setpoint for the next time step, MPC considers the effects of all possible interventions and chooses the strategy that most closely follows the setpoint for a longer period into the future.

MPC is able to predict the future behavior of the plant and optimize a control strategy for a certain period. Two significant time horizons can therefore be identified. First, the optimization horizon is the amount of timesteps the MPC controller considers in the optimization of the control strategy. Second,

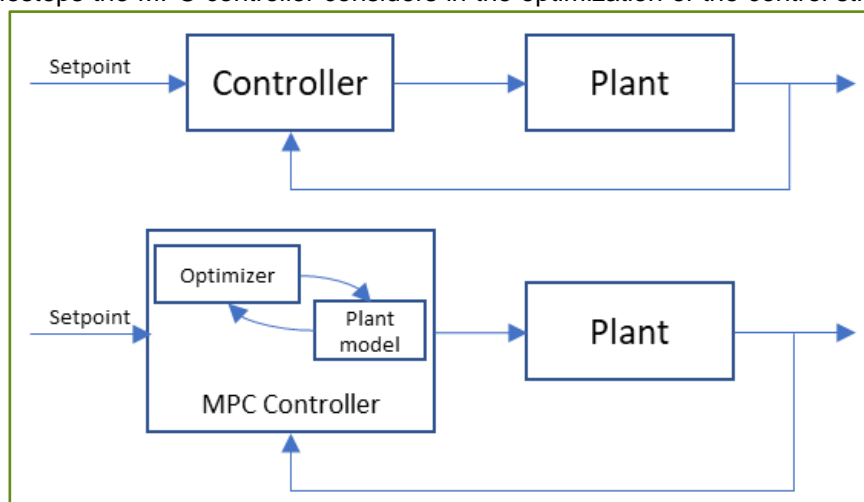


Figure 36: Basic feedback control and Model Predictive Control (after (MathWorks, 2018))

the control horizon is the amount of timesteps to which the optimized control strategy is actually applied. Tuning of these horizons is essential to the operation of the algorithm in terms of accuracy and calculation time. A large optimization horizon significantly increases the simulation time of the optimizer. Even a linear optimization scheme increases exponentially in simulation time with the size of the control problem. Furthermore, the prediction of the output behavior determined in the model of the plant of the MPC controller has decreasing accuracy of increasing time into the future. The decreasing accuracy with increasing optimization horizon leads to tuning requirement of the control horizon. The control horizon is generally smaller, and never larger than the optimization horizon (MathWorks, 2018).

Application of MPC to the operation of the hybrid power plant allows for intelligent storage and settlement strategies based on the input of renewed wind power production forecasts. Such a control sequence for distributed generation and energy storage technologies has been suggested by Arnold and Andersson (Arnold & Andersson, 2011). A two-level control scheme is suggested for day-ahead planning and on-line dispatch. The benefits of this approach include the fact that the control strategy can be altered at each iteration based on changing circumstances or market prices. As a result, the balancing and operational costs can be reduced by anticipating future events. The control purpose of MPC applied to the hybrid power plant is maximization of the revenue obtained by trading. Control variables are the charge and discharge strategy, DAM bid generation and imbalance settlement strategy presented in timeseries with the length of the optimization horizon. The optimized strategy is implemented up to the control horizon, at which point the process is repeated with renewed wind power generation forecasts. Additional requirements for this approach are the expected market prices corresponding to the Day Ahead Market and imbalance settlement.

### Development of an MPC algorithm for the hybrid power plant

A Model Predictive Control algorithm is designed to simulate the day to day operation of the hybrid power plant. The algorithm is based on the exact same model of the power plant as discussed in chapter 5. However, the difference in optimization and control horizons requires an additional time identifier and a restructuring of the model. Furthermore, where the battery capacity optimization algorithm ran on existing data containing a DAM obligation for each time step, the proposed operational algorithm must be able to generate the DAM bid. Therefore, two modules are introduced: A DAM module and an intraday module.

### Nomenclature

As the MPC algorithm is significantly different from the battery capacity optimization algorithm, some new terms are introduced. Two unique time identifiers are relevant to the problem. First of all, each execution, or iteration, of a module is represented by a consecutive number, referred to as 'run'. Each run of the algorithm optimizes the control strategy up to the optimization horizon and implements all timesteps up to the control horizon. The timestep for which the optimization is executed is referred to as a primary time unit (PTU), similar to the terminology used in phase one of this study. Figure 37 is an illustration of the two time identifiers. Subsequent runs are presented by the horizontal bars, where each PTU is represented by a single square within that bar (a PTU in a run). The fading color of subsequent PTU's represents the decreasing accuracy of the represented value. It is important to note the difference

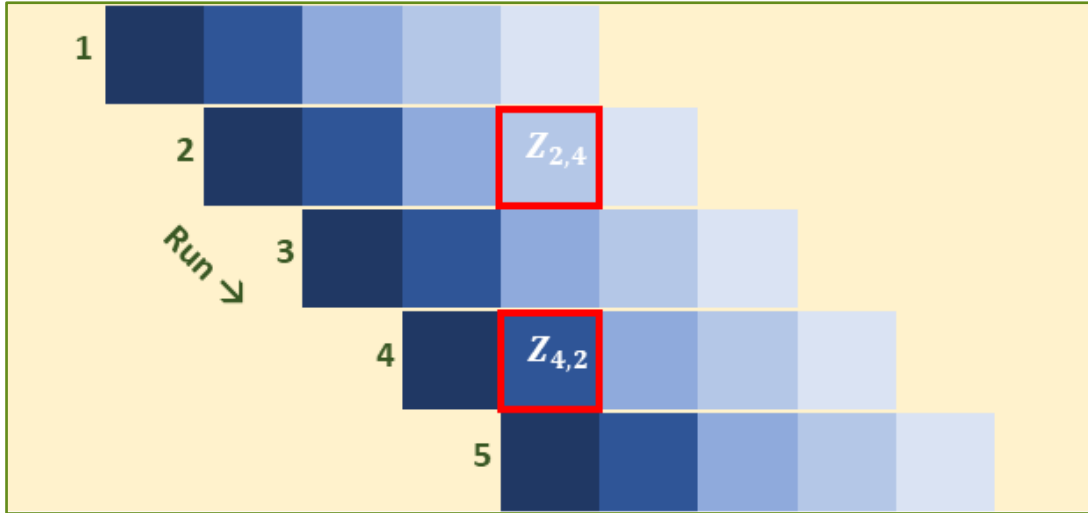


Figure 37: The horizontal bars represent subsequent runs, with the first run at the top. All runs execute the optimization for a horizon of 5 timeslots

between the squares  $Z_{2,4}$  and  $Z_{4,2}$ ; while they technically refer to the exact same timeslot, their values will likely not be the same due to the fact that each run is executed based on renewed information on wind power generation and battery level.

While two individual modules for the overall MPC algorithm are introduced, the nomenclature for both modules are the same. Therefore, Table 12 and Table 13 present the parameters and variables used in the MPC algorithm. Runs are identified by the first subscript of a variable or parameter and in general terms presented by  $t$ . The PTU within a run is presented by the second subscript and in general terms presented by  $t'$ . For example, the battery level determined by the 5<sup>th</sup> run for the 10<sup>th</sup> PTU in that run is denoted by  $BL_{5,10}$ .  $\underline{\underline{E}}^{act}$  has the same function in the MPC algorithm as  $\underline{\underline{E}}^{act}$  in the battery capacity optimization algorithm. However, since the MPC algorithm does not run on perfect forecast,  $\underline{\underline{E}}^{act}$  is a forecast matrix based on actual production of a wind farm. The matrix is structured in such a way that each row represents a new run of the algorithm. The first item in row  $t$  reflects the forecast at time  $t$  for the first PTU, the second item in that row is the power generation forecast for the second PTU in that run, and so on up to the optimization horizon. The market prices presented by  $\underline{\underline{EMP}}^{DAM}$  and  $\underline{\underline{EMP}}^{imbalance}$  are expected price profiles for the respective markets. Simulation of realistic operation means that the energy prices in the relevant markets are not available beforehand, and market price approximations are required. Both the data and assumptions regarding  $\underline{\underline{E}}^{act}$  and  $\underline{\underline{EMP}}$  are discussed in the 'Simulation set-up' section of this chapter. Since the previous algorithm established the optimal battery capacity for the hybrid power plant, it is considered a constant input parameter in the MPC algorithm. As a result, the CAPEX is an input parameter as well, while OPEX is still a variable in the objective function of both modules since it is charge schedule dependent.

Table 12: Hybrid power plant MPC parameters

Parameter	Unit	Description
<b>BC</b>	$\left[\frac{EUR}{MWh}\right]$	Battery installation cost
<b>BS</b>	[MWh]	Battery size (volume capacity)
<b>CAPEX</b>	[EUR]	Capital expenditures
<b>CL</b>	[-]	Battery cycling life in number of full charge/discharge cycles
<b>DOD</b>	[%]	Maximum allowable depth of discharge
$E_{t,t'}^{act}$	[MWh]	True (or expected) production at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2,..T\}$
$EMP_{t,t'}^{DAM}$	$\left[\frac{EUR}{MWh}\right]$	Expected Day Ahead Market price at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2,..T\}$
$EMP_{t,t'}^{imbalance}$	$\left[\frac{EUR}{MWh}\right]$	Expected export price at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2,..T\}$
$\eta^c$	[%]	Charge efficiency
$\eta^d$	[%]	Discharge efficiency
$h_1$	[-]	Optimization horizon DAM module expressed in number of PTU's
$h_2$	[-]	Optimization horizon intraday module expressed in number of PTU's
<b>LT</b>	[-]	Battery lifetime expressed in number of PTU's
$MP_{t,t'}^{DAM}$	$\left[\frac{EUR}{MWh}\right]$	True Day Ahead Market price at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2,..T\}$
$MP_{t,t'}^{imbalance}$	$\left[\frac{EUR}{MWh}\right]$	True imbalance price at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2,..T\}$
<b>NC</b>	[MWh]	Net connection capacity expressed in maximum allowable PTU volume
<b>R<sub>OC</sub></b>	[-]	Ratio of OPEX to CAPEX
<b>T</b>	[-]	Simulation time expressed in number of executed runs
<b>TF</b>	[-]	Total fraction of battery capacity faded at end-of-life

Table 13: Hybrid power plant MPC variables

Variable	Unit	Description
$BL_{t,t'}$	[MWh]	Battery level at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$CF_{t,t'}$	[MWh]	Capacity fade due to cycling at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$E_{t,t'}^C$	[MWh]	Positive charge volume at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$E_{t,t'}^D$	[MWh]	Positive discharge volume at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$E_{t,t'}^{DAM}$	[MWh]	DAM obligation based on bid at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$E_{t,t'}^{export}$	[MWh]	Positive volume sold to imbalance market at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$E_{t,t'}^{imbalance}$	[MWh]	Net volume settled on the imbalance market at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$E_{t,t'}^{import}$	[MWh]	Positive volume purchased from imbalance market at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$
$OPEX_{t,t'}$	[EUR]	Operational expenditures
$t$	[–]	Current run identifier
$t'$	[–]	Specific PTU within a run
$TC_{t,t'}$	[MWh]	Total volume previously charged at PTU $t' \in \{1,2,..h\}$ within run $t \in \{1,2, ... T\}$

### Hybrid power plant MPC formulation

While the full MPC algorithm is structured through two individual modules, the underlying model of the hybrid power plant is the same. The model of the hybrid power plant as presented in chapter 5 is valid for the MPC algorithm as well, the same constraints and equations apply. However, a restructuring reflecting the two time axes (runs and PTU's in a run) is required. The MPC formulation of the model is presented below, the additional equations required for the two modules are presented later on in this section.

#### Energy balance and net connection cable

The first three equations closely resemble equation 5.2 to 5.4. Equation 6.4 calculates the net imbalance settlement. The proposed MPC algorithm assumes equal imbalance export and import prices, therefore a net imbalance variable is required. A negative imbalance means  $E_{t,t'}^{import} > E_{t,t'}^{export}$ .

$$\forall t \in \{1,2, ... T\}, \forall t' \in \{1,2, ... h_i\}, i \in \{1,2\}:$$

$$E_{t,t'}^{act} + \eta^D E_{t,t'}^D + E_{t,t'}^{import} = E_{t,t'}^{DAM} + E_{t,t'}^C + E_{t,t'}^{export} \quad (6.1)$$

$$E_{t,t'}^{DAM} + E_{t,t'}^{export} \leq NC \quad (6.2)$$

$$E_{t,t'}^{import} \leq NC \quad (6.3)$$

$$E_{t,t'}^{imbalance} = E_{t,t'}^{export} - E_{t,t'}^{import} \quad (6.4)$$

### Battery level definition and charging limits

Where equation 5.5 relates the current battery level to the battery level of the previous PTU, MPC requires a relation between subsequent runs as well as a relation between subsequent PTU's. Equation 6.5 achieves this by taking the battery level of the first PTU of the previous run (since it is implemented to the plant) and the charge and discharge schedules within the current run. For the first run, an initial value of the battery level is required. The battery level and charge and discharge limits are similar to the battery capacity optimization model. Total charge, defined by equation 6.9 corresponds to the cumulative charge from the first run to the current run.

$$\forall t \in \{1, 2, \dots, T\}, \forall t' \in \{1, 2, \dots, h_i\}, i \in \{1, 2\}:$$

$$BL_{t,t'} = BL_{t-1,1} + \sum_{t_2=1}^{t'} [\eta^c E_{t,t_2}^c - E_{t,t_2}^d] \quad (6.5)$$

$$BL_{t,t'} \geq \left(50\% - \frac{DOD}{2}\right) \cdot BS \quad (6.6)$$

$$BL_{t,t'} \leq \left(50\% + \frac{DOD}{2}\right) \cdot BS - CF_{t,t'} \quad (6.7)$$

$$CF_{t,t'} = \frac{TF}{CL} \frac{n}{LT} TC_{t,t'} \quad (6.8)$$

$$TC_{t,t'} = \sum_{t_1=1}^t E_{t_1,1}^c \quad (6.9)$$

$$E_{t,t'}^c \leq \frac{BS}{4} \quad (6.10)$$

$$E_{t,t'}^d \leq \frac{BS}{4} \quad (6.11)$$

$$E_{t,t'}^c \leq E_{t,t'}^{act} \quad (6.11)$$

### DAM module

This module has the objective of establishing the DAM bid (and obligation) at every 12:00 occurrence of the simulation. The performed bid is based on the forecast at that time for the next day. The optimization horizon for the DAM module is therefore 36 hours (144 PTU's), including the 12 hours up to the next day and all 24 hours of that next day. The objective function governing this module only considers Day Ahead Market income and the operational costs of charging the battery system. Imbalance trading is irrelevant since imbalance by definition does not occur. The input parameters include an expected price series on an hourly basis, as is the structure of the market. Other parameters, such as the initial battery level at the start of the next day, must be extracted from the most recent intraday module execution. The last battery level in the optimization result is taken to be the initial battery level of the next day. Price variations in this market lead to storage incentives.

$$\text{maximize} \sum_{t'=1}^{h_1} [EMP_{t,t'}^{DAM} E^{DAM}] - OPEX(TC_{t,t'}) \quad (6.12)$$

$$OPEX(TC_{t,t'}) = \frac{R_{oc} BC}{CL} TC_{t,t'} \quad (6.13)$$

## Intraday module

The intraday module more closely resembles the battery capacity optimization algorithm, since it operates on an established DAM bid and imbalance emerges through deviations in wind power production. Since the final battery level in the last execution of this module before 12:00 must correspond with the initial battery level of the next day, the optimization horizon is established at 12 hours (48 PTU's). Equation 6.13 is valid for both modules. A crucial assumption within the intraday module states that the imbalance prices of exporting and importing are equal to each other, which is true for approximately 90% of the time. This simplifies the objective function, as presented below.

$$\text{maximize } \sum_{t'=1}^{h_2} [EMP_{t,t'}^{imbalance} E_{t,t'}^{imbalance}] - OPEX(TC_{t,t'}) \quad (6.14)$$

## Validation

The DAM module is validated by providing fabricated expected market price series. For a constant market price, it is expected that the battery system will not serve a function, since there's no potential increase in value of stored energy. The optimization variable  $\underline{\underline{E}}^{DAM}$  must therefore correspond to the input parameter  $\underline{\underline{E}}^{act}$ . For a market price that increases linearly throughout the day, it is expected that energy is stored in the battery since the highest energy value is obtained at the end of the day. However, as soon as the battery is full, the optimization variable  $E^{DAM}$  must correspond to the input parameter  $E^{act}$ . Finally, for a market price that decreases linearly throughout the day, there is once again no incentive to store energy, and the optimization variable  $E^{DAM}$  must correspond to the input parameter  $E^{act}$ . These hypotheses are tested for four distinct days throughout the year. The process and results are extensively presented in Appendix 2. Since no deviation from the expected behavior occurs, the DAM module is validated. The intraday module requires no additional validation, since the algorithm matches the battery capacity optimization algorithm. Validation of this algorithm is discussed in chapter 5, and shown in Appendix 1.

## MPC execution schedule and revenue calculation

The execution scheme of the MPC algorithm is depicted in Figure 38. This scheme is iterated up to the final timestep in the simulation. Execution of the DAM module happens each day at 12:00, simultaneously with the intraday module for that timestep. Figure 39 illustrates a full day timeline of the MPC algorithm. Each hour, depicted by a single block in the bottom timeline, the intraday module is executed based on hour-to-hour updates of wind power generation forecasts. This is represented by the closeup, where the hours are divided into 15-minute intervals, the primary time unit or PTU. Four PTU's pass before the next forecast is available, and therefore the first four PTU's of the optimized charging and settlement schedule is truly implemented. The rest of the optimized variables is scheduled. While this schedule may not truly be implemented, it is crucial to the functioning of the MPC algorithm that future behavior is anticipated, otherwise, only the first four PTU's would be optimized with no regard to future developments in market price or power generation, resulting in suboptimal overall behavior. The DAM optimization module is executed each day at 12:00, based on expected price series of this market.



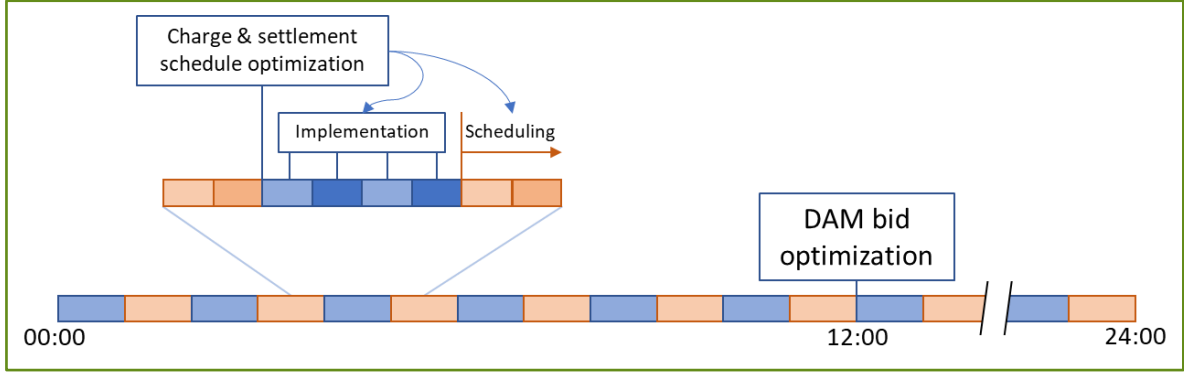


Figure 39: MPC timeline depicting both intraday and DAM module

Optimization of the DAM obligation, charge/discharge and imbalance settlement schedule is performed on the basis of expected price series, since the price series are published after execution of the respective module. Revenue calculation can therefore only be performed after execution of the algorithm based on true price series. These price series are the same that are used in chapter 5, and the revenue calculation is similar as well. Trading revenue is determined by multiplying the implemented DAM and imbalance settlement schedules with their corresponding true market prices. CAPEX is a given, since the battery capacity is a constant parameter, as is the battery installation cost in EUR/MWh. OPEX is determined by summing the first four PTU's of the charge variable of each run (implemented results, as illustrated in Figure 39) for the whole simulation. The reduced revenue is equal to the trading revenue minus the CAPEX and OPEX.

$$Revenue = \sum_{t=1}^T \sum_{t'=1}^4 [MP_{t,t'}^{DAM} E_{t,t'}^{DAM} + MP_{t,t'}^{imbalance} E_{t,t'}^{imbalance}] \quad (6.15)$$

$$Profit = R_t - CAPEX - OPEX \quad (6.16)$$

$$CAPEX = \frac{T}{LT} BC \cdot BS \quad (6.17)$$

$$OPEX = \frac{R_{oc} BC}{CL} \sum_{t=1}^T \sum_{t'=1}^4 E_{t,t'}^C \quad (6.18)$$

### Simulation set-up

Simulation of the MPC algorithm has once again been performed for each individual year of the available dataset provided by Ecofys. However, instead of using the exact market obligation, power production and market price data, forecasts have to be generated. Before presenting the results, generation of wind power production forecasts and assumptions regarding market price inputs are discussed. All simulations are performed for a battery capacity of 70 MWh, as established by the previous optimization sequence. The battery is assumed to be fully discharged at the beginning of each simulation,  $BL_{0,1} = 0$ .

## Wind power generation forecast

The proposed MPC algorithm requires wind power production forecast data with a maximum horizon of 36 hours as dictated by the DAM module. It is desirable that the same years are simulated as in the battery capacity optimization simulations, however, no meteorological data regarding forecasts is available. Therefore, a different approach is taken by generating forecast data based on an increasing Root Mean Square Error (RMSE) with time into the future. A forecast generation model has been made available by Ecofys which is able to generate hour-to-hour forecasts. The true power generation timeseries serves as input of this model, and if multiple datasets from different geographical locations are available, the model is able to generate forecasts based on geographical correlation between the two sites. No second set of data is available, other than that of the onshore wind farm used before. Therefore, no geographical correlation is applied to the generation of forecast data, only the increasing RMSE technique. Figure 40 shows the resulting forecast error for a 36-hour horizon for the year 2009. The black line shows the true production, which is equal to the forecast generation model input. The red dotted line shows the forecast after one hour has passed for the subsequent 35 hours. As expected,

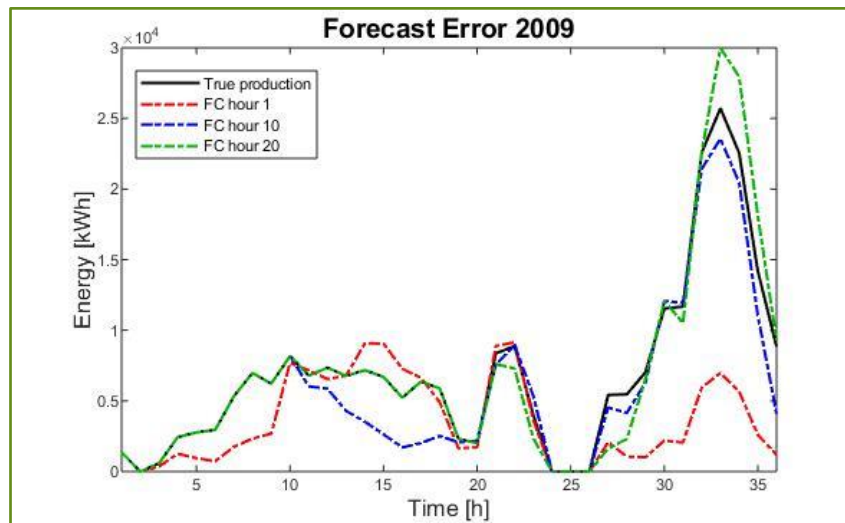


Figure 40: Forecast accuracy for a 36 hour period

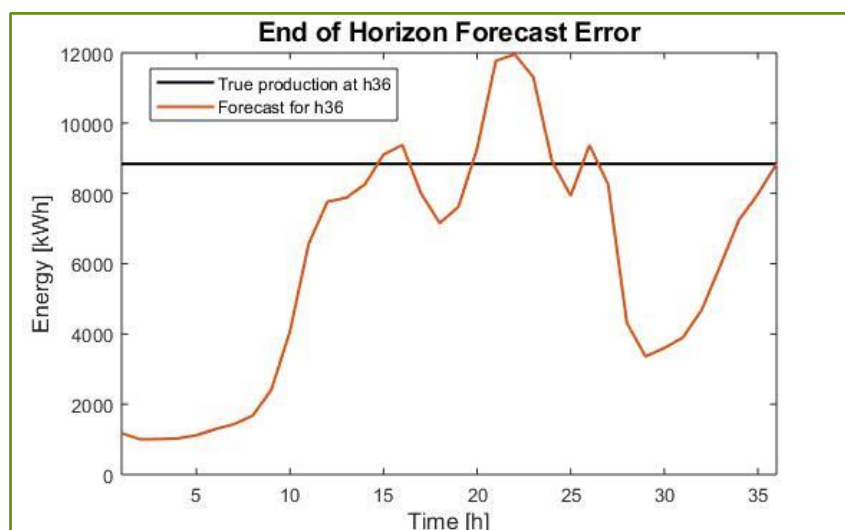


Figure 41: Forecast accuracy for a single timeslot

the error (difference between red line and black line) is largest at the end of the horizon. The blue and green dotted lines show the forecasts at 10 and 20 hours respectively.

Figure 41 shows the forecast accuracy from another point of view. The same period is considered as in the previous figure; however, the forecast and true output of a single hour are considered. A period of one-and-a-half day is considered, from 00:00 on day one to 12:00 on day two. The constant black line indicates the *true output* at 12:00 on day two. The red line indicates expected generation for that same time based on the forecast algorithm at the time in hours indicated on the x-axis. While the expected generation fluctuates around the true generation as a function of time, it can be concluded that for decreasing distance to the considered timeslot, the forecast becomes more accurate.

### Market price forecasts

The market prices used in both the DAM as well as the intraday module are not available beforehand, and the assumption of perfect foresight is invalid in the development of a day-to-day tool. Therefore, additional assumptions are required regarding the DAM prices and the imbalance settlement prices. A data analysis is performed on historic data to capture the market characteristics and propose a typical price profile approximation for both markets. The data used in this analysis consists of the price series of all available wind power production data years (2009 – 2015). For validation and comparison purposes, a reference case is tested using the assumption of perfect foresight. In this case, the market price profiles used in the objective functions of the DAM and intraday module correspond to the actual market prices published after the time of execution.

The first approach is to take the average weekend and weekday market price profiles and use these as an approximation in the objective function of their respective modules. The resulting price profiles of the Day Ahead Market and the imbalance market are presented in Figure 42 and Figure 43 on 15-minute interval basis. At first glance, it immediately becomes apparent that the energy price is significantly higher during weekdays as compared to weekend days. The average difference between the two DAM profiles is 8.04 EUR/MWh, and the average difference between the two imbalance profiles is 14.05 EUR/MWh.

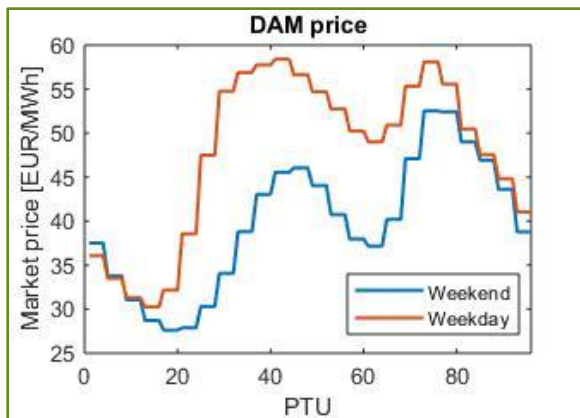


Figure 42: Weekend & weekday DAM market price profiles

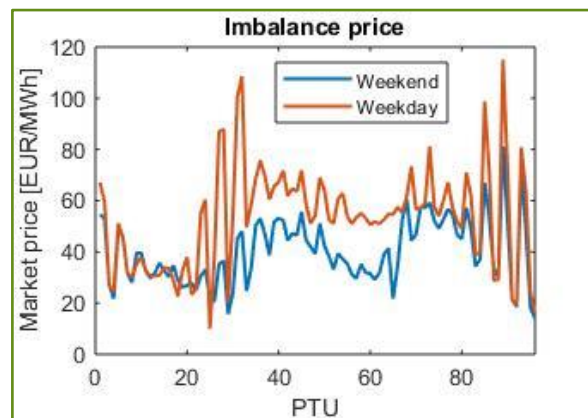


Figure 43: Weekend & weekday imbalance market price profiles

The second approach is to take the average seasonal market price profiles, as presented in Figure 45 and Figure 44. From the DAM seasonal price profiles, the conclusion can be drawn that the price of energy in the spring and summer months is significantly lower than in the winter and autumn months. The average DAM price difference between autumn and summer is 4.89 EUR/MWh as is the average difference between autumn and summer imbalance price.

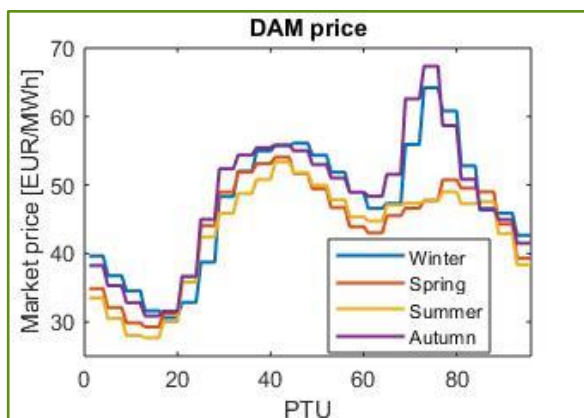


Figure 45: Seasonal DAM market price profiles

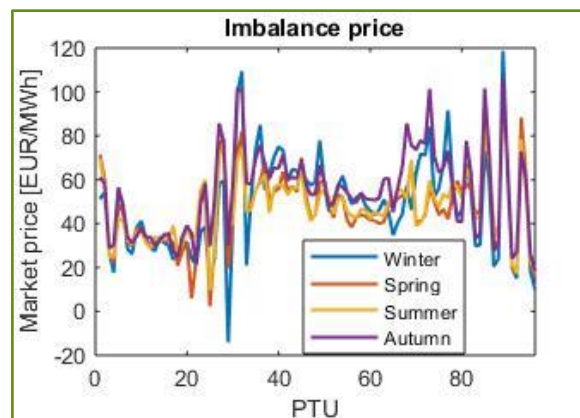


Figure 44: Seasonal imbalance market price profiles

The assumptions of the price profiles are tested against true data to properly judge the validity. For this purpose, the root mean square error (RMSE) between true data and the price profiles from Figure 42 to Figure 44 is calculated for the full length of a single year, paying careful attention to weekend and weekend days or the season, respectively. The results of the assumptions are presented in Table 14. Based on these values, it is difficult to predict the behavior of the algorithm. It is expected that the perfect foresight assumption will perform very well, however, it is only presented for comparison purposes since this assumption is invalid for day-to-day operation. Overall, increased accuracy in the price profile approximation is expected to lead to better performance of the algorithm, especially for the imbalance market prices.

Table 14: RMSE values for market price approximations in [EUR/MWh]

	Perfect Foresight	Weekday/weekend	Seasons
DAM	0	6.57	7.28
Imbalance market	0	24.42	24.38

### DAM obligation establishment

Not only are three market price approximations tested, the establishment of the DAM bid is also varied. Again, three methods are introduced. First, the obligation is established by the DAM module as described in the model formulation. Second, the original wind prediction services (WPS) bid is used, as given in the Ecofys dataset. This bid is taken to be representative of wind farm bidding. Finally, the forecast for the next day as given by the wind power generation forecast model is used.

## Results and analysis

Similar to chapter 5, the profitability of the configuration is determined by the revenue and profit. Since nine scenarios are tested (three market price assumptions and three DAM bid establishment techniques, indicated in Table 15), the results of only three out of seven simulated years are presented according to a 'worst, intermediate, best' classification based on the revenue. The worst performing year in all simulations is 2010, the best performing year 2013, and 2015 is representative of an intermediate performing year. Furthermore, the same terminology is used as in chapter 5, as indicated by Table 16

*Table 15: List of tested scenarios of the MPC module*

<b>Market price method:</b>	<b>DAM bid method:</b>
Perfect Foresight (PF)	DAM module
Perfect Foresight (PF)	WPS
Perfect Foresight (PF)	Forecast
Weekday / weekend (WD/WE)	DAM module
Weekday / weekend (WD/WE)	WPS
Weekday / weekend (WD/WE)	Forecast
Seasonal	DAM module
Seasonal	WPS
Seasonal	Forecast

*Table 16: Terminology used in results of MPC simulations*

<b>Term</b>	<b>Description</b>
<b>Revenue</b>	All earnings from trading energy
<b>Profit</b>	Revenue minus installation and operational costs
<b>Reference revenue</b>	All earnings from trading energy in the reference scenario of trading without a battery
<b>Profitability</b>	Difference between profit and reference revenue, expressed in a percentage of the reference revenue

### Perfect foresight

For analysis and comparison purposes, the assumption of perfect foresight is presented here. It is expected that this configuration of the model will return the best results as compared to the assumption of weekday/weekend and seasonal market prices. Figure 46 shows the results of the worst, intermediate, and best performing year of the MPC algorithm with the DAM module active. This means that at every occurrence of 12:00, the algorithm submits a bid to the Day Ahead Market, optimized according to the charge/discharge strategy and assumed market prices. In all years, trading with the battery storage system performs better than trading without a battery storage system. As expected, the capital and operational expenditures significantly reduce the profit margin, and in the case of 2010, this

results in an unprofitable outcome. 2013 (identified as the best year) and 2015 (reference year) remain profitable, even after subtraction of CAPEX and OPEX from the revenue. The results of the DAM module are mirrored by the WPS DAM bid and the wind power generation forecast DAM bid. Figure 47 and Figure 48 show nearly exactly the same results as Figure 46, and the difference in performance is marginal. The marginality of the difference is confirmed by the profitability values: 22.37%, 22,31% and 22.44% average profitability for the three DAM bid methods, respectively. While the results of only three years are depicted in the figures, it is important to mention that 2010 is the only year returning a negative profit margin of all seven simulated years.

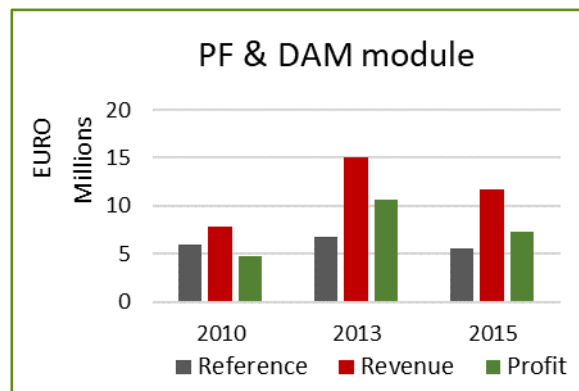


Figure 46: MPC results perfect foresight and DAM module

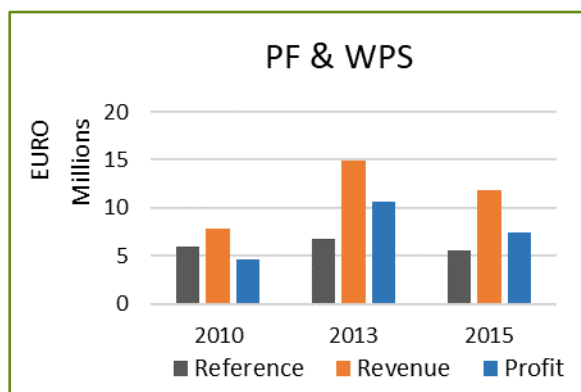


Figure 47: MPC results perfect foresight and WPS bid

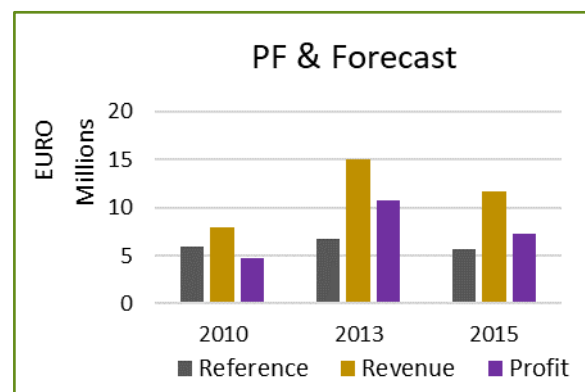


Figure 48: MPC results perfect foresight and DAM bid equals generation forecast

### Weekend and weekday market price profiles

The first realistic assumption regarding market price profiles used in the objective function of the intraday and DAM module (if used) is that of weekday and weekend (WD and WE) profiles. The results are presented in Figure 49, Figure 50 and Figure 51. In all cases, the revenue is higher than the reference revenue, indicating that the storage and settlement strategy is favorable to standard trading mechanisms. However, the battery system costs lead to unprofitable outcomes in all scenarios and all considered years. As in the perfect foresight reference calculations, the differences between the different DAM bid approaches is marginal, and a more detailed approach is required. The average profitability of the three years considered is -29.11%, -29,21% and -29,11% respectively between the three modes of DAM bid establishing.

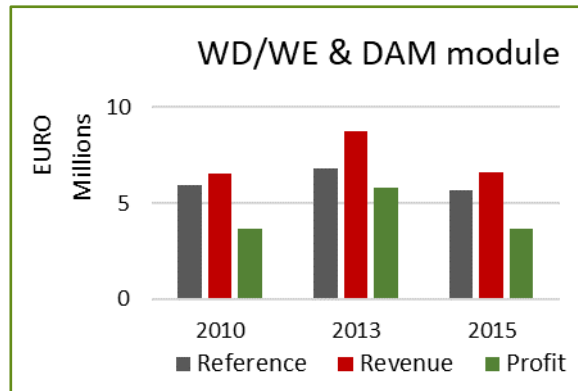


Figure 49: MPC results WD/WE and DAM module

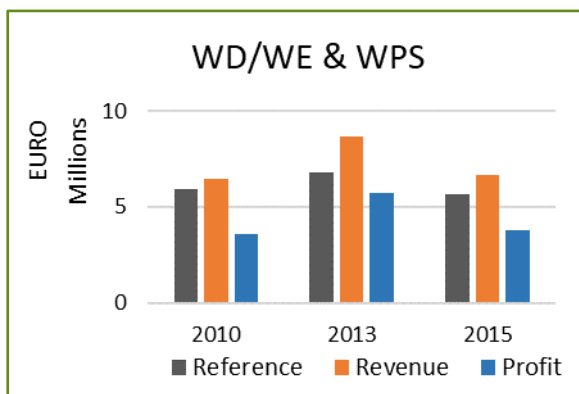


Figure 50: MPC results WD/WE and WPS bid

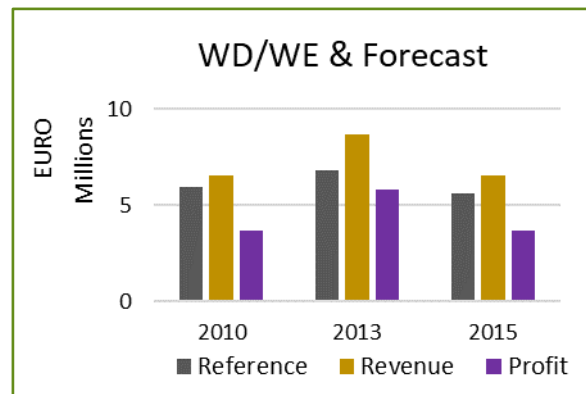


Figure 51: MPC results WD/WE and DAM bid equals generation forecast

### Seasonal market price profiles

Finally, the assumption of seasonal market price profiles is tested for the same set of years. Since the RMSE values for this approach are similar to those of the weekday/weekend approach, it is expected that the difference in outcome between the two is marginal. The results are presented in Figure 52, Figure 53 and Figure 54. The MPC revenue is larger than the reference revenue in all scenarios and years simulated. Nevertheless, the installation and operational costs still outweigh the benefits by a large margin. The average profitability for the three DAM bid scenarios is -31.81%, -31.9% and -31.81% respectively. While the overall profitability is negative, the seasonal market price assumption performs 2% worse than the weekday/weekend market price assumption.

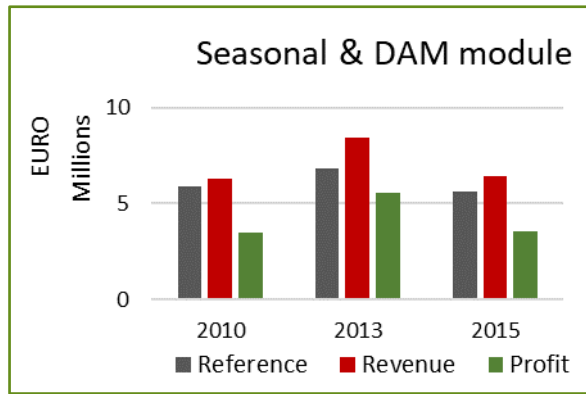


Figure 52: MPC results seasonal market prices and DAM module

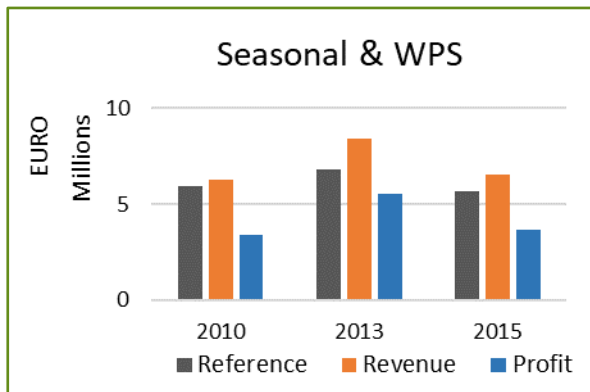


Figure 53: MPC results seasonal market prices and WPS bid

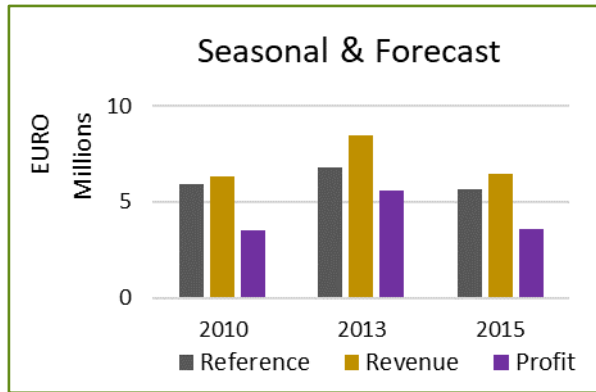


Figure 54: MPC results seasonal market prices and DAM bid equals generation forecast

### Additional results

Based on the presented results, the proposed configuration and operation of the hybrid power plant is unprofitable in all simulations. An important observation, though, is that even in the most unprofitable year and scenario, the revenue of the hybrid power plant is higher than the reference revenue. The cost of installation and operation (CAPEX and OPEX) are too substantial to overcome with the proposed approximations of the market prices. While the optimum battery capacity is determined to be somewhere between 60 and 80 MWh for a 60 MW wind farm, a smaller battery system reduces the costs of installation and operation and may result in a profitable configuration. For the best performing year (2013) and the best performing market price approximation (weekday/weekend), the effect of battery capacity on both trading revenue, as well as reduced revenue is tested. Figure 55 indicates that while the revenue increases for increasing battery capacity, the increased cost of installation and operation cause for decreasing reduced revenue.

For the same year (2013) and scenario (WD/WE and DAM module), the return on investment is determined. From Figure 49, it becomes apparent that the profit of the configuration is less than the reference revenue, and therefore the ROI will be negative. The capital expenses for a 70 MWh battery installation is approximately 2.2 million Euros and the profit is a negative 1 million Euros. Overall, the ROI for this best performing scenario is -46%, indicating the significant loss the investment returns.

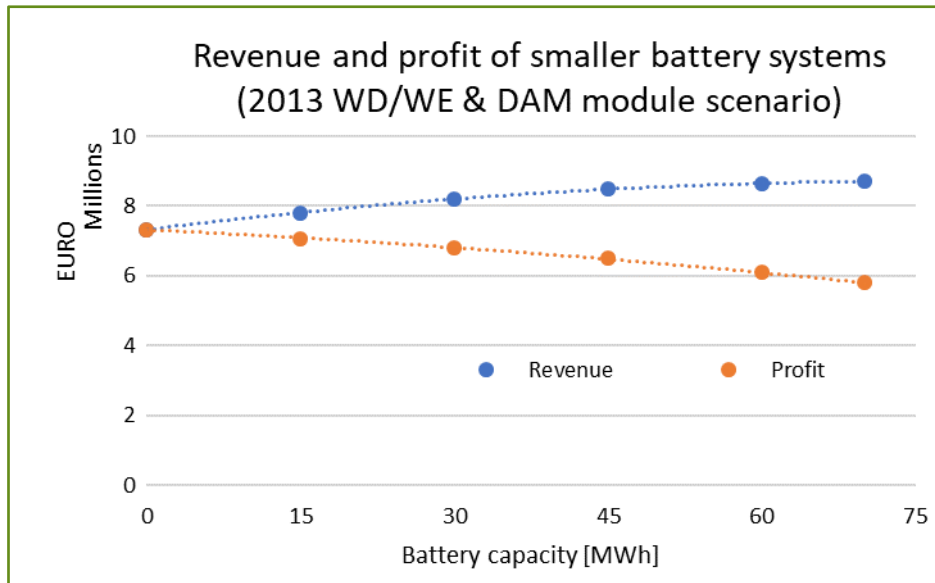


Figure 55: Effect of reduced battery capacity on revenue and profit for WD/WE market price profiles and DAM module in 2013

Considering all results, it can be concluded that Model Predictive Control is a suitable method for hybrid wind farm operation, but not at the proposed market price approximations and battery installation costs. These two factors are required to be able to sustain profitable trade using the battery system. The perfect foresight simulations showed that the revenue increase potential is large for accurate approximations. The significant cost of installation and operation reduce the profitability by a large margin. Cost reduction of lithium-ion battery technologies is expected to increase the feasibility of MPC driven hybrid power plant operation.

## ***Key Takeaways Chapter 6***

- Model Predictive Control is a suitable method for hybrid wind farm operation. It requires both wind power generation forecasts on a regular basis and market price approximations
- MPC requires a model formulation that relates subsequent runs, as well as subsequent PTU's within a single run
- The proposed MPC algorithm makes use of a DAM module, which establishes an optimized Day Ahead Market bid, and an intraday module that optimizes the charge/discharge and imbalance settlement schedule
- Revenue increases significantly for all tested scenarios. The installation and operational costs cause for an overall unprofitable result for the battery capacity range established in chapter 5
- Weekday/weekend or seasonal market price profiles can serve as approximations for the DAM and intraday modules, the former performing only slightly better than the latter
- Hybrid power plants with a reduced battery capacity with respect of the established optimal battery capacity may return profit (compared to the reference scenario)
- Potential drivers for MPC driven hybrid power plant operation are market price approximations of increased accuracy and cost reduction of lithium-ion battery technologies

## Chapter 7: Conclusions

With the development of an operational tool for the hybrid power plant, this study has come to its conclusion. Along with the key takeaways that are presented in the frames at the end of each chapter, this final chapter aims to present a comprehensible overview of the main findings and results with regards to the research drivers and questions. The limitations of the presented models and results are discussed, along with recommendations for future work.

## Recap

Before presenting the conclusions to this study, the research drivers and questions, as laid out in chapter 1, are revisited. A knowledge gap exists on exact configurations of battery energy storage systems as an addition to onshore wind farms, and the role of such a hybrid power plant in the Dutch power market system. This study is therefore driven by the ambition to:

- ❖ Assess the role of battery energy storage for the generation of wind power in the Netherlands
- ❖ Analyze the Dutch power system to identify sources of revenue and trading strategies
- ❖ Develop an operational tool that determines the charging and settlement schedule of the hybrid power plant

These research drivers lead to the formulation of the main research question of this study, and the division into sub questions:

**Q.** *How can battery energy storage be optimally designed and operated for onshore wind farms in the Netherlands?*

**q1.** *What criteria determine whether the hybrid power plant is optimally designed?*

**q2.** *Which wind power and battery characteristics influence the optimization criteria established in q1?*

**q3.** *Which energy markets are relevant to the hybrid power plant?*

**q4.** *What is the optimal configuration of the hybrid power plant?*

**q5.** *How can the hybrid power plant be optimally operated on a daily basis?*

## Conclusions

### *Optimal hybrid power plant design*

While battery energy storage systems are able to provide valuable services to the generation of wind power and other intermittent renewable sources, optimal design is judged by the profitability of a configuration and trading strategy. Separation between generation and supply of power allows for intelligent trading strategies leading to value increase of power generated at low real-time pricing. Additionally, since a power plant has a balance responsibility based on their market obligation, the reduction of imbalance is a key design parameter. Imbalance of a power plant caused by a mismatch between generation and obligation must be settled at elevated and volatile imbalance prices. Reduction of imbalance is therefore able to increase profitability of the proposed hybrid power plant.

### *Wind power and battery characteristics*

On multiple timescales, the variable nature of wind power production can lead to a mismatch between instantaneous supply and demand. The daily power generation profile, along with the power demand

profile and corresponding market prices, leads to chances for increased value of energy through energy storage. Short-term intermittency caused by sudden variations in wind speed can cause voltage dips, harmonic voltage variation and flicker. These phenomena require additional power electronics when connecting a turbine or a wind farm to the grid, and battery energy storage is reported to be able to fulfill these ancillary services, both on plant as well as grid operator level.

Lithium-ion battery technology is characterized by its wide range of energy and power ratings and high overall efficiency. Nickel manganese cobalt oxide and iron phosphate technologies demonstrate overall good performance and potential for utility scale energy storage applications. As a direct result of the (de)-intercalation mechanism, rapid or deep (dis)charging can lead to mechanical stresses within the electrodes, causing accelerated degradation of the battery's volume and power capacities. Safe and prolonged operation of battery energy storage systems require careful attention to the applied conditions, and maximum current ratings and depth of discharge are formulated to achieve this. Additionally, round-trip efficiency, calendar life, cycling life and installation costs all influence the operation and performance of battery energy storage systems.

#### *Dutch power markets*

In total, six power markets can be identified: bilateral trade agreements, the Day Ahead Market, the Intraday Market, and three balancing mechanisms operated by the TSO: FCR, aFRR and mFRR. Only three of these six markets are accessible for power trade with the hybrid power plant due to the bidding schedule, power requirements and price incentives: The Day Ahead Market, and the FCR and aFRR imbalance markets. Assuming no bilateral trade agreements, the Day Ahead Market is the primary market on which energy is traded and it establishes the supply obligation of the plant. The primary frequency restoration mechanism operated by the national TSO, TenneT, is the FCR market. The compensation for accepted capacity bids is substantial and this market is therefore an attractive platform for the hybrid power plant since the battery system can ensure the offered capacity is available throughout the duration of the obligation. aFRR is the second frequency regulation mechanism operated by TenneT. It is characterized by highly fluctuating prices and a settlement frequency of 4 times per hour. While the average price on this market is similar to the DAM price, the size of the fluctuations leads to potentially profitable trading strategies.

#### *Optimal design of the hybrid power plant*

Optimal design is judged by the level of imbalance and the profitability of the proposed configuration. Modelling of the hybrid power plant assures that the obligation to the Day Ahead Market is maintained, either aided by the battery or conventionally settled at imbalance prices. Accessible power markets are modelled by means of their price series, based on a perfect-foresight assumption, and corresponding limitations. Due to uncertainties regarding the acceptance and activation of FCR bids, this market is not considered in the model, leaving only the Day Ahead Market and the aFRR market. The constraints derived from the system characteristics and the assumptions are translated into a set of linear equations which, with the addition of an objective function, serves as an optimization algorithm. The objective of the linear optimization algorithm is to find the battery capacity in MWh that returns the highest profit, considering the installation and operation costs. First, of the two battery technologies identified, nickel

manganese cobalt oxide (NMC) performs better than the alternative (LFP). For a 60 MW windfarm in the Netherlands, the optimal battery capacity lies within the range of 60 – 80 MWh, returning a revenue increase of 14 – 20% compared to the reference scenario. An overview of the obtained results is presented in Table 17.

*Table 17: Multiple year simulation results NMC battery capacity optimization model for a 60 MW wind farm*

	Simulated range	Optimal battery capacity [MWh]	Revenue increase [%]
	2010 – 2013	60 – 70	14
	2011 – 2014	60 – 80	17
	2012 – 2015	70 – 80	20

*Optimal operation of the hybrid power plant*

A Model Predictive Control approach is proposed to deal with wind power generation forecasts with increasing accuracy in time. Both a weekday/weekend as well as a seasonal market price approach is tested, both demonstrating similar RMSE values with actual market price data. Additionally, three techniques of establishing the DAM obligation are employed. In all tested cases, the MPC revenue is higher than the reference revenue. However, consideration of the installation and operational costs of the battery system leads to unprofitable results in all tested cases. The weekday/weekend market price profile performs slightly better than the seasonal market price profile approximation. Potential factors that could increase the profitability of the system are market price profile approximations with increased accuracy (lower RMSE values) and cost reduction of battery energy storage systems. All in all, the simulations with the best results are based on the weekend/weekday market price profiles and the DAM optimization module active. An overview of the obtained results is presented in Table 18.

*Table 18: Best results obtained by MPC simulations for three individual years*

Year	Reference revenue [10 <sup>6</sup> EUR]	Trading revenue [10 <sup>6</sup> EUR]	Trade increase [%]	Reduced revenue [10 <sup>6</sup> EUR]	Profitability [%]
2010	5.93	6.55	23.77	3.68	-37.97
2013	6.80	8.71	27.99	5.80	-14.73
2015	5.63	6.59	16.99	3.68	-34.67

Answer to the research question

**Q.** *How can battery energy storage be optimally designed and operated for onshore wind farms in the Netherlands?*

Battery energy storage can be employed to aid short term-intermittency issues posed by connecting a wind farm to the power grid. These issues include loss of power quality and an overall mismatch between supply and demand on a maximum timescale of one day. Currently, nickel manganese cobalt oxide batteries show the best overall performance for utility scale energy storage applications. The required battery capacity for a 60 MW wind farm lies within the range of 60 – 80 MWh, depending on the imbalance market price variation. Operation of the hybrid power plant can be performed using Model Predictive Control to optimize the charge and imbalance settlement strategy for a fixed optimization and control horizon. However, inaccurate market price profile approximations and high cost of battery installation and operation currently leads to unprofitable employment.

### *Reflection*

The study by Balischewski et. al indicated that energy storage systems could be highly beneficial to the wind energy resource provided that configuration optimization is executed. Operational strategies are not discussed in that paper. Arnold and Andersson suggest the use of a two-level Model Predictive Control strategy to deal with day-ahead and real-time energy trade and found that MPC operation could significantly reduce the operating costs. The battery capacity optimization sequence performed in this study, along with the suggested MPC algorithm elaborate on the suggestions of the mentioned papers and the findings in this study partially confirm the results of those papers. The MPC revenue is higher than the reference revenue in all cases considered and costs of balancing are thereby reduced. The Arnold and Andersson study recommended market price approximations of increased accuracy for future MPC operation of the energy storage systems considered. This study found that market price approximations of high accuracy result in highly profitable operation. However, the market price approximations that are used in the simulations proved to be of insufficient accuracy.

### **Limitations**

While the battery capacity optimization and the MPC algorithms adequately simulate the behavior of the hybrid power plant for the purposes of this study, several limitations apply. Elaboration on these limitations serve as a guide on how to interpret the results of this study, and how to use the proposed models.

#### *Regarding wind farm modelling*

It has been stated that battery systems can aid wind farms in the short term intermittency and provide ancillary services to the hybrid power plant operator as well as to the grid. However, since both the power production data as well as market price profiles are supplied with a 15-minute resolution, battery action on a shorter timescale is not modelled. It may be assumed that, while power requirements are relatively high for these ancillary services, the timescale of such services is significantly small to leave the battery level nearly unaffected.

One of the main assumptions of this study is the fact that the hybrid power plant is designed for an existing wind farm. Accordingly, net connection cable costs are not considered since it poses no extra costs to the installation of a battery system. It has been indicated that battery energy storage could lead to decreased capacity requirements for the net connection cable in the development of new wind farms. Elaboration of the battery capacity optimization algorithm could include the net connection cable as an optimization variable, enabling reduced connection costs of a new hybrid power plant. Additionally, this allows for intelligent congestion management for both plant and grid operator.

#### *Regarding battery system modelling*

Some battery characteristics are left out of the model. Energy and power densities are deemed irrelevant, since no spatial constraints are assumed in the design of the hybrid power plant. Self-discharge of the system is negligibly small and is therefore not considered. Furthermore, it is assumed that the maximum C-rate is equal to one, meaning the system takes at least one hour to fully charge or discharge. Depending on the use case for which the battery is deployed, faster charging or discharging

may be desired. Application of the proposed models (both design as well as operation) for other use cases will require alteration of these parameters.

#### *Regarding system costs*

The battery costs are approximated by the installation cost in EUR/kWh and the operational costs are derived from this value. The battery installation cost is spread out linearly over the lifetime of the system and the yearly costs are taken to be equal to the total cost divided by the lifetime. These approximations proved sufficient to indicate the feasibility of the optimal configuration as well as the optimal operation of the hybrid plant. For the development of a business case, one of the requirements is to provide a more accurate financial model considering interest, inflation, net present value and payback time.

#### *Regarding market prices*

The battery capacity optimization algorithm as presented in chapter 5 assumed perfect foresight, both regarding wind farm power generation as well as for market prices. The operational tool presented in chapter 6 assumed market price profiles based true market data. Within the changing landscape of power production in the Netherlands, it is expected that the structure of the power markets will adjust accordingly, as will the price levels. Increased variability in the production of power could lead to increased variability in the (imbalance) market prices, which bodes well for the performance of the models presented in this study. However, the effect of the transformation of the energy system on the relevant power markets is uncertain, and for future development, market price approximation is a key focus area.

#### *Regarding results*

Since it is established that the profitability of the hybrid power plant is highly dependent on the variability of the imbalance market price, the results between the simulated years are relatively large. Furthermore, all of the simulations performed for the operational tool proved to be unprofitable. However large the margin established by energy trade, the cost of installation and operation of the hybrid power plant is too large. The limitations of the models therefore include the reliance on the imbalance market price variability for both models, and the battery installation cost most notably for the operational model. The obtained results can therefore not be used as a blueprint for hybrid power plant operation but do fulfill the research objectives stated at the beginning of this study.

## Recommendations

The presented limitations to the design and operational model pave the way for recommendations regarding future work. For future work and application of the operational tool, three key focus areas are identified.

- ❖ Accurate financial modelling
- ❖ Addition of the FCR market
- ❖ Accurate market price approximations

While the battery capacity optimization model clearly indicates the feasibility of battery assisted energy trading, supported by the increased trading revenue of the operational model, the true cost of ownership of such a system has been disregarded. This study serves as an adequate starting point for additional

research and application of other use cases. However, to create a sustainable business plan based on the two models presented in this report, financial modelling of higher accuracy is desired. The cost of the system as presented in this study is simply the installation cost determined by a single cost parameter. In reality, the purchase of a cost intensive battery system requires a large investment, likely financed by a bank loan. In that case, compound interest significantly drives up the cost of ownership, as does the inflation over the duration of the systems lifetime.

Due to the uncertainties regarding bid acceptance and activation, the FCR market has been left out of the current models. However, with an average capacity price of 2000 – 3000 EUR/MWh (on a weekly basis), the potential benefits of operating on this market is significant. The current models could be elaborated by engaging this market, requiring additional input parameters characterizing the FCR market. Furthermore, the likely change from a weekly to a daily tender needs to be accounted for in the adjustment of both algorithms used in this study.

The operational tool presented in this study makes use of market price profile approximations. While two approximations are tested (weekend/weekday and seasonal), the simulations that used perfect foresight indicated the necessity of accurate market price profiles. The results using the approximations returned no profit in any case, whereas the perfect foresight approach was highly profitable, except for the year 2010. It is expected that market price profile approximations of increased accuracy allow for a more intelligent and profitable charging and imbalance settlement strategy. Recommended strategies include studying weather dependent market profiles, market price transition probabilities, and machine learning. Weather dependent market profiles requires a correlation between weather conditions and market prices, enabling projections of market prices based on weather forecasts. A market price transition probability approach would be able to determine the price level of the next PTU based on the current and previous PTU's. A machine learning approach would combine the previous two approaches to be able to predict the market price for an oncoming period based on both weather data as well as current and historic market prices.

Execution of these recommendations can serve as an important step in the development and operation of hybrid power plants.

## References

- ACM. (2015). *Systeemcode Elektriciteit*. Autoriteit Consument & Markt.
- Albright, G. (2012). *A Comparison of Lead Acid to Lithium-ion in Stationary Storage Applications*. AllCell Technologies LLC.
- Allen, M., Dube, O., Solecki, W., Aragón-Durand, F., Cramer, W., Humphreys, S., . . . Zickfeld, K. (2018). Framing and Context. *Global warming of 1.5°C. An IPCC Special Report*. The Intergovernmental Panel on Climate Change.
- Arnold, M., & Andersson, G. (2011). Model Predictive Control of Energy Storage including Uncertain Forecasts. *17th Power Systems Computation Conference*. Stockholm.
- Balischewski, S., Hauer, I., Wolter, M., Wenge, C., Lombardi, P., & Komarnicki, P. (2017). Battery Storage Services that Minimize Wind Farm Operating Costs : A Case Study. *IEEE PES Innovative Smart Grid Technologies Europe*. Turin: ISGT Europe.
- Bosch & van Rijn. (2018). *Statistieken*. Retrieved October 30, 2018, from WindStats: <https://windstats.nl/statistieken/>
- Breeze, P. (2016). The Anatomy of a Wind Turbine. In P. Breeze, *Wind Power Generation* (pp. 19-27). Academic Press.
- Bresser, D., Paillard, E., & Passerini, S. (2015). Lithium-ion batteries for medium- and large-scale energy storage: current cell materials and components. In D.Bresser, E.Paillard, & S.Passerini, *Advances in Batteries for Medium- and Large-scale Energy Storage* (pp. 125 - 211). Woodhead Publishing Series in Energy.
- Broussely, M., Biensan, P., Bonhomme, F., Blanchard, P., Herreyre, S., Nechev, K., & Staniewicz, R. (2005). Main aging mechanisms in Li ion batteries. *Journal of Power Sources, volume 146*, 90-96.
- Buchmann, I. (2018). *Types of Lithium-ion Batteries*. Retrieved September 5, 2018, from Battery University: [https://batteryuniversity.com/learn/article/types\\_of\\_lithium\\_ion](https://batteryuniversity.com/learn/article/types_of_lithium_ion)
- Bussel, G. J. (2008, October 1). Power Quality. *Wind Energy Online Reader*. Delft.
- Chang, M. (2018). *Flexibiliteit op de elektriciteitsmarkt*. Movares MJA-SPIDeR.
- Chen, H., Cong, T. N., Yang, W., Tan, C., Li, Y., & Ding, Y. (2009). Progress in electrical energy storage system: A critical review. *Progress in Natural Science, volume 19*, 291 - 312.
- Consentec. (2014). *Description of load-frequency control concept and market for control reserves*. Aachen: Consentec GmbH.
- de Vries, L. (2018). Electricity: Market design and policy choices. *Reader for the course SEN1521*. Delft: Delft University of Technology.
- Díaz-González, F., Sumper, A., Gomis-Bellmunt, O., & Villafafila-Robles, R. (2012). A review of oenergo storage technologies for wind power applications. *Renewable and Sustainable Energy Reviews, volume 16*, 2154-2171.
- Dicorato, M., Forte, G., Pisani, M., & Trovato, M. (2012). Planning and Operating Combined Wind-Storage System in Electricity Market. *IEEE transactions on sustainable energy, volume 3*, 209-217.
- DOE. (2018). *Grid Modernization and the Smart Grid*. Retrieved January 15, 2019, from Office of Electricity: <https://www.energy.gov/oe/activities/technology-development/grid-modernization-and-smart-grid>

- DOE. (2018). *Learn More About Interconnections*. Retrieved January 15, 2019, from Office of Electricity: <https://www.energy.gov/oe/services/electricity-policy-coordination-and-implementation/transmission-planning/recovery-act-0>
- ECN. (2017). *Nationale Energieverkenning 2017*. Amsterdam/Petten.
- EIA. (2015, Februari 25). *Wind generation seasonal patterns vary across the United States*. Retrieved December 20, 2018, from U.S. Energy Information Administration: <https://www.eia.gov/todayinenergy/detail.php?id=20112>
- Energieia. (2017, May 18). *Onbalanshandel maakt wind plus batterij rendabel*. Retrieved December 20, 2018, from Windunie: <https://www.windunie.nl/onbalanshandel-maakt-wind-plus-batterij-rendabel/>
- EPEX Spot. (2018). *EPEX SPOT Power NL Day Ahead*. Retrieved October 18, 2018, from <https://www.apxgroup.com/market-results/apx-power-nl/dashboard/>
- Feng, X., Ouyanga, M., Liu, X., Lu, L., Xia, Y., & He, X. (2018). Thermal runaway mechanism of lithium ion battery for electric vehicles: A review. *Energy Storage Materials journal, volume 10*, 246 - 267.
- Fox, B., Flynn, D., Bryans, L., Jenkins, N., Milborrow, D., O'Malley, M., . . . Anaya-Lara, O. (2007). *Wind Power Integration - Connection and System Operational Aspects*. London: The Institution of Engineering and Technology.
- Glaze, C., & Geniès, S. (2013). *Lithium Batteries and Other Electrochemical Storage Systems*. London: ISTE LTd.
- Government of the Netherlands. (2018, March 19). *Nuon wins permit for Dutch offshore wind farm without subsidy*. Retrieved January 29, 2019, from Government.nl: <https://www.government.nl/latest/news/2018/03/19/nuon-wins-permit-for-dutch-offshore-wind-farm-without-subsidy>
- Hansen, A. D. (2017). Wind Turbine Technologies. In T. M. Letcher, *Wind Energy Engineering* (pp. 145 - 160). London: Academic Press.
- Huggins, R. A. (2016). *Energy Storage*. Springer International Publishing Switzerland.
- IEA. (2011). *Harnessing Variable Renewables*. Paris: OECD.
- IEA. (2017). *World Energy Outlook 2017*. International Energy Agency.
- IRENA. (2017). *Electricity Storage and Renewables: Cost and Markets to 2030*. Abu Dhabi: International Renewable Energy Agency.
- IRENA. (2018). *Renewable Power Generation Costs in 2017*. Abu Dhabi: International Renewable Energy Agency.
- Jiang, Q., Gong, Y., & Wang, H. (2013). A Battery Energy Storage System Dual-Layer Control Strategy for Mitigating Wind Farm Fluctuations. *IEEE transactions on power systems*, 3263-3273.
- Klein Entink, M. (2017). *Benefits of local electrical energy storage for a distribution system operator*. Delft: Delft University of Technology.
- Kouskou, T., Bruel, P., Jamil, A., El Rhafiki, T., & Zeraouli, Y. (2014). Energy storage: Applications and challenges. *Solar Energy Materials & Solar Cells, volume 120*, 59-80.
- Letcher, T. M. (2017). Why Wind Energy? In T. M. Letcher, *Wind Energy Engineering* (pp. 3 - 14). London: Academic Press.

- Li, X., Hui, D., & Lai, X. (2013). Battery Energy Storage Station (BESS)-Based Smoothing Control of Photovoltaic (PV) and Wind Power Generation Fluctuations. *IEEE transactions on sustainable energy*, 464-473.
- Lowe, M. (2010). *Lithium-ion Batteries for Electric Vehicles: the U.S. Value Chain*. Durham: ResearchGate.
- Ly, P. H. (2018). *The Economics of a District Battery*. Delft: Delft University of Technology.
- Mahmud, N., & Zahedi, A. (2016). Review of control strategies for voltage regulation of the smart distribution network with high penetration of renewable distributed generation. *Renewable and Sustainable Energy Reviews*, 582-595.
- MathWorks. (2018). *MATLAB overview*. Retrieved November 6, 2018, from MathWorks: <https://nl.mathworks.com/products/matlab.html>
- MathWorks. (2018, december). *Understanding Model Predictive Control*. Retrieved from Video and Webinar Series: <https://www.mathworks.com/videos/series/understanding-model-predictive-control.html>
- McLaren, J. (2016, April 13). *Batteries 101 Series: How to Talk About Batteries and Power-To-Energy Ratios*. Retrieved February 4, 2019, from NREL Transforming Energy: <https://www.nrel.gov/state-local-tribal/blog/posts/batteries-101-series-how-to-talk-about-batteries-and-power-to-energy-ratios.html>
- MIT. (2008, December). A Guide to Understanding Battery Specifications. MIT Electric Vehicle Team.
- Navigant Research. (2017). *Market Data: EV Market Forecasts*. Navigant Consulting, Inc.
- NEXT Kraftwerke. (2018). *A nearly complete list of European TSOs*. Retrieved november 15, 2018, from NEXT Kraftwerke: <https://www.next-kraftwerke.com/knowledge/european-tsos-list>
- Nitta, N., Wu, F., Lee, J. T., & Yushin, G. (2015). Li-ion battery materials: present and future. *Materials Today*, volume 18, 252 - 264.
- NS. (2017). *NS Jaarverslag*. Nederlandse Spoorwegen.
- Pillot, C. (2017). *The Rechargeable Battery Market and Main Trends 2016-1025*. Avicenne Energy.
- Rahmann, C. (2017). Break-Even Points of Battery Energy Storage Systems for Peak Shaving Applications. *Energies*, volume 10, 833 - 846.
- Reihani, E., Motalleb, M., Ghorbani, R., & Saad Saoud, L. (2016). Load peak shaving and power smoothing of a distribution grid with high high renewable energy penetration. *Renewable Energy*, volume 86, 1372-1379.
- Rijksdienst voor Ondernemend Nederland. (2018a). *Windenergie op land*. Retrieved January 29, 2019, from RVO: <https://www.rvo.nl/onderwerpen/duurzaam-ondernemen/duurzame-energie-opwekken/windenergie-op-land>
- Rijksdienst voor Ondernemend Nederland. (2018b). *Windenergie op Zee*. Retrieved January 29, 2019, from RVO: <https://www.rvo.nl/subsidies-regelingen/stimulering-duurzame-energieproductie/categorie%C3%ABn/windenergie-op-zee>
- Roland Berger. (2012). *Technology & Market Drivers for Stationary and Automotive Battery Systems*. Nice, France.
- Schüwer, D. (2018). Electrification of industrial process heat: long-term applications, potentials and impacts. *ECEEE Industrial Summer Study Proceedings 2018* (pp. 411 - 422). Berlin: ECEEE.
- Sinden, G. (2007). Characteristics of the UK wind resource: Long-term patterns and relationship to electricity demand. *Energy Policy*, 112-127.

- Sociaal-Economische Raad. (2019). *Ontwerp van het Klimaatakkoord*. Den Haag: Ministerie van Economische Zaken en Klimaat.
- Sørensen, P. (2007). Power Fluctuations From Large Wind Farms. *IEEE transactions on power systems*.
- Staffell, I., & Rustomji, M. (2016). Maximising the value of electricity storage. *Journal of Energy Storage, volume 8*, 212-225.
- Stan, A.-I., Swierczynski, M., Stroe, D.-I., Teodorescu, R., & Andreasen, S. J. (2014). Lithium Ion Battery Chemistries from Renewable Energy Storage to Automotive and Back-up Power Applications - An Overview. *2014 International Conference on Optimization of Electrical and Electronic Equipment* (pp. 713 - 720). Bran: IEEE.
- TenneT. (2018). *System & transmission data*. Retrieved November 20, 2018, from TenneT: [https://www.tennet.org/english/operational\\_management/](https://www.tennet.org/english/operational_management/)
- UNFCCC. (2019). *What is the Paris Climate Agreement*. Retrieved January 23, 2019, from United Nations Climate Change: <https://unfccc.int/process-and-meetings/the-paris-agreement/what-is-the-paris-agreement>
- Wang, J., Purewal, J., Liu, P., Hicks-Garner, J., Soukazian, S., Sherman, E., . . . Verbrugge, M. W. (2014). Degradation of lithium ion batteries employing graphite negatives and nickel-cobalt-manganese oxide + spinel manganese oxide positives: Part 1, aging mechanisms and life estimation. *Journal of Power Sources, volume 269*, 937-948.
- Wang, W., Wang, D., Gordin, M., & Choi, D. (2010). Lithium-ion Batteries for Stationary Energy Storage. *JOM: the journal of the Minerals, Metals & Materials Society, volume 62*, 24 - 30.
- Yang, Y. (2018). Battery energy storage system size determination in renewable energy systems: A review. *Renewable and Sustainable Energy Reviews, 109-125*.
- Yao, D. (2012). Schedule for a Wind Farm Incorporated With Dual-Battery Energy Storage Scheme. *IEEE transactions on sustainable energy*.
- Zhai, Q., Meng, K., Dong, Z. Y., & Ma, J. (2017). Modeling and Analysis of Lithium Battery Operations in Spot and Frequency Regulation Service Markets in Australia Electricity Market. *IEEE transactions on industrial informatics, volume 13*, 2576-2586.

## Appendix 1: Battery capacity optimization algorithm Validation

The validity of the battery capacity optimization model is tested against the reference scenario presented in chapter 5 under assumption 9. It is expected that for exorbitant battery prices, the potential revenue increase will not be able to account for the installation and operational costs of the system. The optimization algorithm will therefore return an optimal battery capacity of 0 MWh, and the trading revenue will be equal to the reference revenue. Simulations are performed for all seven years of data, at the original wind farm power capacity of 60 MW. The battery installation cost is multiplied by a factor 10 to achieve unprofitable results in any case where the battery capacity is more than 0 MWh.

*Table A 1: Validation of battery capacity optimization model*

<i>Year</i>	<i>Optimized battery capacity [MWh]</i>	<i>Revenue increase [%]</i>
2009	0	0.12097
2010	0	0.26054
2011	0	0.16062
2012	0	0.42822
2013	0	-0.58334
2014	0	-0.74978
2015	0	-0.80838

Table A 1 indicates that, indeed, the battery capacity for high installation and operational costs is equal to 0 MWh. However, there is a revenue increase or decrease for all years. The source of this discrepancy lies in the inequality between the imbalance settlement of the reference scenario as opposed to the optimized strategy. In some cases, when the price of exporting and importing energy is unequal, the optimization algorithm chooses to settle the net imbalance in the most favorable market, both importing and exporting energy. The net settlement (import – export) corresponds to the reference settlement (=imbalance), but it is not necessarily true that only import *or* export can obtain a value. This phenomenon happens 7.4% of all PTU's simulated and leads to a revenue increase discrepancy of less than 1%. It is therefore considered to be within allowable limits.

Table A 2 illustrates the settlement schedule for a half day, for both the reference scenario and the optimization algorithm. The highlighted rows indicate inequalities between the two. While the import and export values are not equal between the two schedules, the difference between import and export (imbalance) in the third and sixth column of the table do fully correspond. In the illustrated case in the table, such an inequality occurs 3 out of 36 PTU's, slightly more than the overall 7.4%.

Table A 2: Comparison between optimization algorithm and reference scenario

	Reference			Optimization algorithm		
	Import	Export	Difference	Import	Export	Difference
1	0	2.544	-2.544	0	2.544	-2.544
2	0	2.919	-2.919	0	2.919	-2.919
3	0	2.61	-2.61	0	2.61	-2.61
4	0	2.135	-2.135	0	2.135	-2.135
5	0	1.853	-1.853	0	1.853	-1.853
6	0.604	0	0.604	0.604	0	0.604
7	0.219	0	0.219	0.219	0	0.219
8	0	0.644	-0.644	0	0.644	-0.644
9	0	0.954	-0.954	0	0.954	-0.954
10	0	0.648	-0.648	0	0.648	-0.648
11	0	1.076	-1.076	0	1.076	-1.076
12	0	0.936	-0.936	0	0.936	-0.936
13	0	0.513	-0.513	10.532	11.045	-0.513
14	0	0.512	-0.512	0	0.512	-0.512
15	0	1.213	-1.213	10.582	11.795	-1.213
16	0	2.159	-2.159	0	2.159	-2.159
17	0	1.235	-1.235	0	1.235	-1.235
18	0	1.28	-1.28	0	1.28	-1.28
19	0	1.531	-1.531	11.264	12.795	-1.531
20	0	1.383	-1.383	0	1.383	-1.383
21	0	0.495	-0.495	0	0.495	-0.495
22	0	2.222	-2.222	0	2.222	-2.222
23	0	1.985	-1.985	0	1.985	-1.985
24	0	2.347	-2.347	0	2.347	-2.347
25	0	2.438	-2.438	0	2.438	-2.438
26	0	0.066	-0.066	0	0.066	-0.066
27	1.971	0	1.971	1.971	0	1.971
28	2.359	0	2.359	2.359	0	2.359
29	2.199	0	2.199	2.199	0	2.199
30	1.964	0	1.964	1.964	0	1.964
31	3.065	0	3.065	3.065	0	3.065
32	3.25	0	3.25	3.25	0	3.25
33	2.973	0	2.973	2.973	0	2.973
34	2.435	0	2.435	2.435	0	2.435
35	1.362	0	1.362	1.362	0	1.362
36	1.798	0	1.798	1.798	0	1.798
37	1.846	0	1.846	1.846	0	1.846
38	1.874	0	1.874	1.874	0	1.874

## Sensitivities

### Wind farm power capacity

The optimization algorithm is based on linear relations regarding the energy balance, battery constraints and objective function. Therefore, the output (optimal battery capacity) must scale linearly with the input (wind farm production data). Simulations are performed in which the original wind farm data is scaled to correspond to 20, 40, 60 and 80 MW. The average battery capacity over all seven years is calculated, and the results are presented in Figure A 1 **Error! Reference source not found.**. The optimal battery capacity scales linearly with the wind farm power capacity. A linear equation relating the battery capacity to the wind farm power capacity is determined, and presented by equation A1.i, a perfect match with the trendline in Figure A 1.

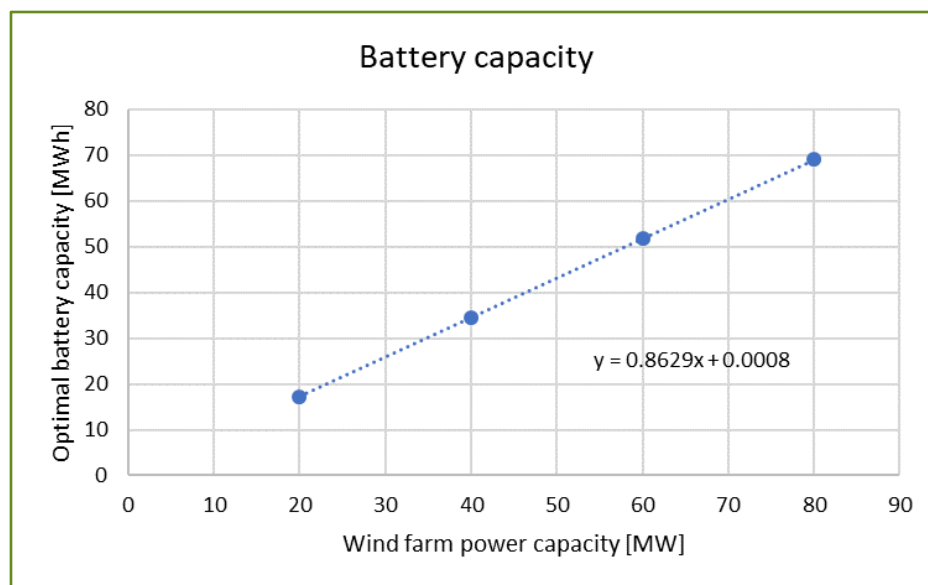


Figure A 1: Correlation between optimal battery capacity and wind farm power capacity

$$Y = 0.8629X + 0.0008 \quad (A1.i)$$

### Assumption of perfect foresight

The market prices used in the optimization of the battery capacity correspond 100% with the true market prices, as stated by the assumption of perfect forecast. The effect on the outcome is tested here by means of altering the market price input parameters with a random distribution over the true market prices. The optimization sequence is repeated for the randomized market prices, and the resulting, optimized market volumes are then multiplied with their respective true market prices to obtain the true revenue. The difference in outcome serves as an indication of the sensitivity. All simulated years are tested for a market price deviation of 5%, 10% and 15%. Table A 3, Table A 5 and Table A 4 show the results of the simulations with the altered market prices. The alternative revenue is the revenue obtained by the optimization algorithm with the altered (5%, 10% and 15% random deviation) market prices. The true revenue is the revenue obtained by the optimized trading time series and the true market prices. The difference between them is presented in a percentage of the true revenue.

*Table A 3: Revenue deviation for 5% market price error*

<i>Year</i>	<i>True Revenue [10<sup>6</sup> EUR]</i>	<i>Alternative Revenue [10<sup>6</sup> EUR]</i>	<i>Difference [%]</i>
2009	5.52	5.83	5.58
2010	5.94	6.32	6.38
2011	8.44	8.82	4.53
2012	7.65	8.08	5.63
2013	9.17	9.61	4.81
2014	6.69	7.06	5.54
2015	6.40	6.81	6.39

*Table A 4: Revenue deviation for 10% market price error*

<i>Year</i>	<i>True Revenue [10<sup>6</sup> EUR]</i>	<i>Alternative Revenue [10<sup>6</sup> EUR]</i>	<i>Difference [%]</i>
2009	5.50	6.17	12.07
2010	5.94	6.72	13.13
2011	8.42	9.19	9.17
2012	7.63	8.50	11.42
2013	9.16	10.07	9.96
2014	6.68	7.45	11.45
2015	6.39	7.21	12.92

The data presented in the tables enable several observations. First, for an increasing market price error, the alternative revenue calculated with those altered market prices increases as well. On average, the difference in alternative revenue between a 5% and a 15% error is 10.52%. Second, for an increasing market price error, the true revenue decreases slightly, with a difference of 0.43% between the 15% and 5% market price error. As a result of the only slightly decreasing true revenue, and the relatively strongly increasing alternative revenue, the difference between the two strongly increases with increasing market price error.

Table A 5: Revenue deviation for 15% market price error

Year	True Revenue [10 <sup>6</sup> EUR]	Alternative Revenue [10 <sup>6</sup> EUR]	Difference [%]
2009	5.48	6.49	18.27
2010	5.93	7.13	20.28
2011	8.39	9.59	14.24
2012	7.61	8.91	17.08
2013	9.14	10.51	15.04
2014	6.67	7.82	17.24
2015	6.36	7.60	19.42

The objective of this analysis is not to test the validity of the perfect foresight assumption, since it can be stated that it is invalid (the plant operator does not have access to all future market prices). However, the analysis has shown that accurate market price forecasting has two advantages. Most evidently, accurate market price forecasting results in a higher obtained revenue. Additionally, accurate market price forecasting results in accurate revenue forecasting.

## Appendix 2: Operational tool

### Validation DAM module

Validation of the algorithm is performed by controlling the input variables in such a way that the outcome of the algorithm can be predicted. The model is considered to be valid when no significant deviation from the expected behavior occurs.

The DAM module determines the market obligation for the next day based on expected price series and the current power generation forecast for the next day. The control variable for the day-ahead market module is the corresponding market price. The market price in the model has a distinct curve, but for validation purposes, three extreme cases are investigated. First, the market price is held constant throughout the day, second, the market price goes up in equal steps, and third, the market price decreases in equal steps. Four days are chosen to represent the behavior of the hybrid power plant. A weekend day in January, a weekday in January, a weekend day in July and a weekday in July. The market prices for these days are presented in Figure A 2 and Figure A 3, and the corresponding power generation forecasts are presented in Figure A 4 and Figure A 7.



Figure A 4: Power generation forecast for Saturday 02-01-2010



Figure A 5: Power generation forecast for Tuesday 05-01-2010

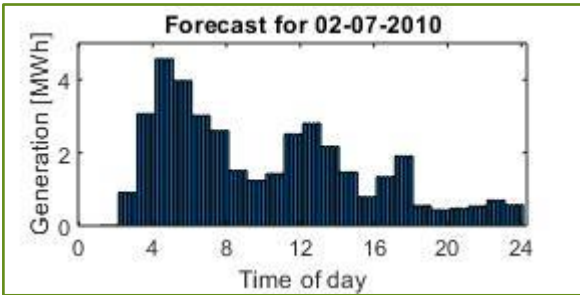


Figure A 6: Power generation forecast for Friday 02-07-2010

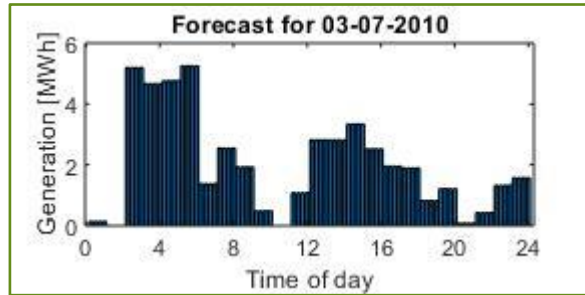


Figure A 7: Power generation forecast for Saturday 03-07-2010

### Constant market price

If the market price is held constant throughout the day, the value of the produced energy does not change. The storage system allows for separation between generation and supply, and therefore potentially increased value of produced energy. However, if the market price is held constant, it is expected that the storage system does not serve a role in the establishment of the day-ahead market price. Therefore, the expected DAM bid resulting from the module is to sell all produced power instantaneously. One important note is that the initial battery level in a run of the DAM module equals the battery level from the latest intraday module iteration at the 12<sup>th</sup> hour. However, since the intraday module optimizes the trading up to a certain horizon, it is expected that the battery is fully discharged at the final hour of the run.



Figure A 8: Market price held constant on a weekday at the average price level of figure A 2



Figure A 9: Market price held constant on a weekend-day at the average price level of figure A 3

*Hypothesis: For a constant market price in the day-ahead market, the battery will not serve a function within this module. Therefore  $E^{DAM}$  will equal  $E^a$ .*

The hypothesis has been tested for four separate scenarios, weekday and weekend day in both the first and seventh month of the year. All results in Figure A 10 to Figure A 13 confirm the hypothesis that if the market price is held constant, the battery will serve no role in the optimization of the battery level given that the battery is at its discharged state at the start of the optimization sequence.

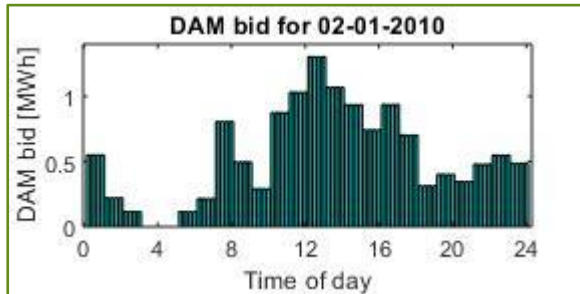


Figure A 10: Optimized DAM bid for Saturday 02-01-2010

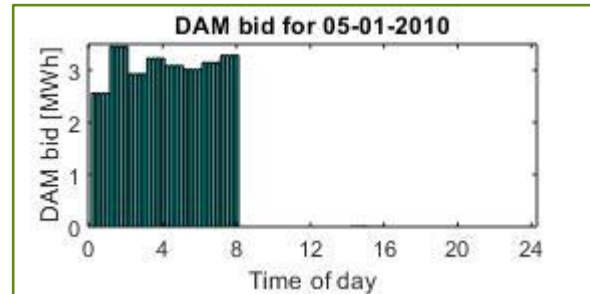


Figure A 11: Optimized DAM bid for Tuesday 05-01-2010

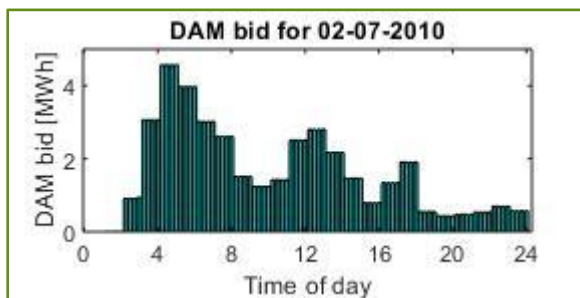


Figure A 12: Optimized DAM bid for Friday 02-07-2010

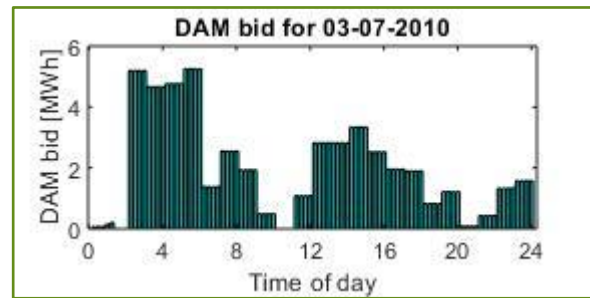


Figure A 13: Optimized DAM bid for Saturday 03-07-2010

### Market price ramp-up

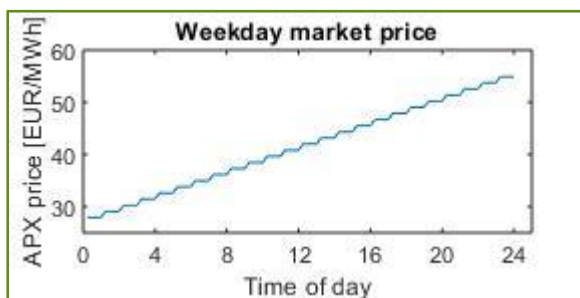


Figure A 14: Fabricated market price for an average weekday. Linear increase from minimum to maximum value of an average weekday

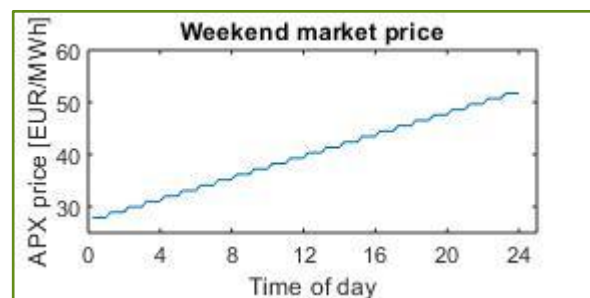


Figure A 15: Fabricated market price for an average weekend day. Linear increase from minimum to maximum value of an average weekend day

*Hypothesis: The market price increases from the start to the end of the day. Therefore, the value of energy at the 24<sup>th</sup> hour is significantly higher than at the 1<sup>st</sup> hour. The battery will store the produced energy at the beginning of the day, until the battery is full. At that time, the plant will sell the produced*

energy instantaneously. At the final hours of the day, the battery will discharge and sell the energy at the high prices (within the constraints of the net connection capacity).

The same days are analyzed as in the 'constant market price' scenario. Therefore, the forecasts are the same, and only the DAM result is presented Figure A 16 to Figure A 19. In all cases, the battery is charged in the beginning of the day, until the battery is full. When the battery is fully charged, the produced energy is directly bid to the day-ahead market. Between hour 22 and hour 24, the battery is

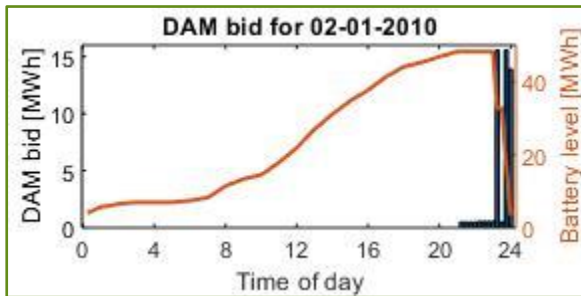


Figure A 16: Optimized DAM bid (left axis) and battery level (right axis) for Saturday 02-01-2010 for the ramp-up scenario

discharged, and this energy is bid to the day-ahead market along with the wind farm production. For the same four cases as in the previous scenario, the hypothesis is once again confirmed for this scenario.

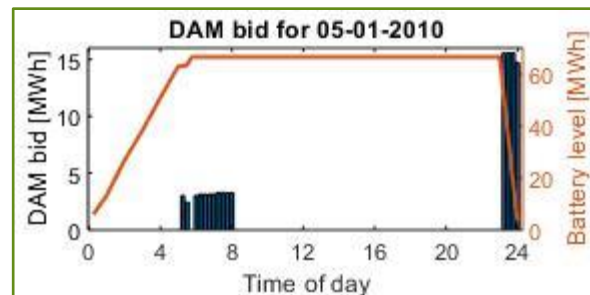


Figure A 17: Optimized DAM bid (left axis) and battery level (right axis) for Tuesday 05-01-2010 in the ramp-up scenario

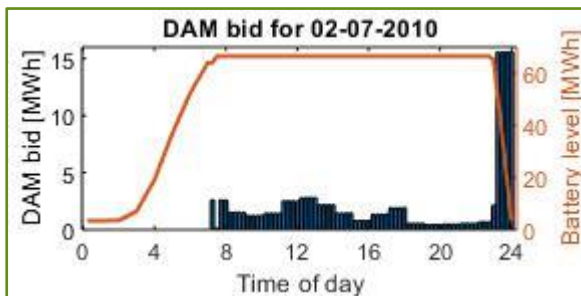


Figure A 18: Optimized DAM bid (left axis) and battery level (right axis) for Friday 02-07-2010 for the ramp-up scenario

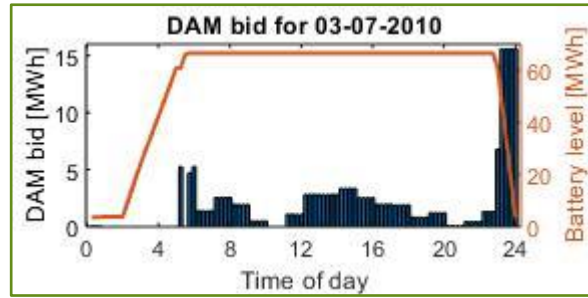


Figure A 19: Optimized DAM (left axis) and battery level (right axis) for Saturday 03-07-2010 for the ramp-up scenario

### Market price ramp-down

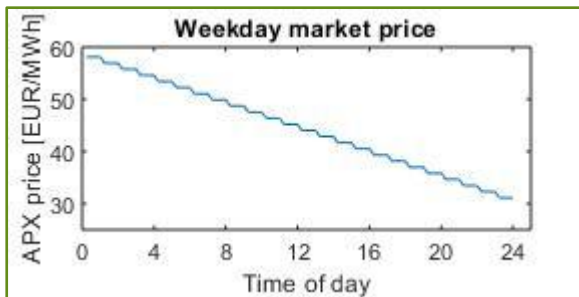


Figure A 20: Fabricated market price for an average weekday. Linear decrease from maximum to minimum value of an average weekday

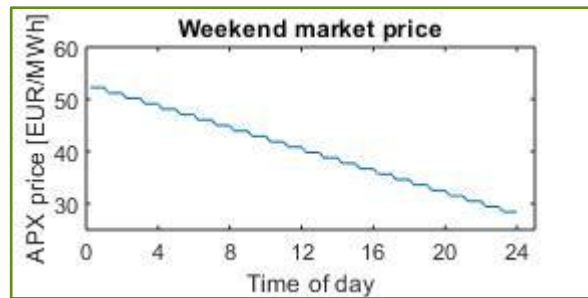


Figure A 21: Fabricated market price for an average weekend day. Linear decrease from maximum to minimum value of an average weekend day

For decreasing market prices throughout the day, the same behavior is expected as in the constant market price scenario since there is no value to storing energy if the price decreases.

*Hypothesis: For a decreasing market price, the generated energy will be instantaneously bid to the day-ahead market;  $E^{DAM} = E^a$ .*

Figure A 22 to Figure A 25 show the exact same behavior as in the constant market price scenario, as expected. The hypothesis is once again confirmed.

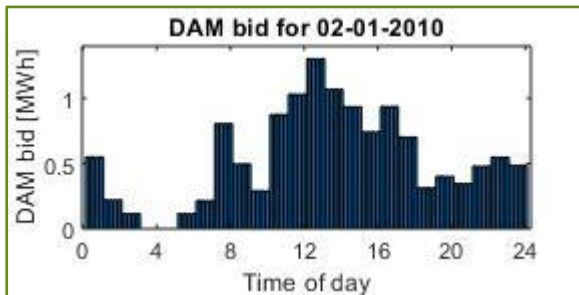


Figure A 22: Optimized DAM bid for Saturday 02-01-2010

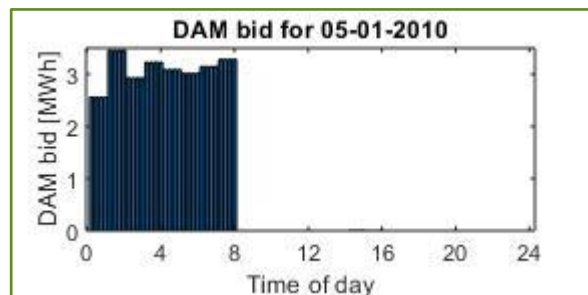


Figure A 23: Optimized DAM bid for Tuesday 05-01-2010

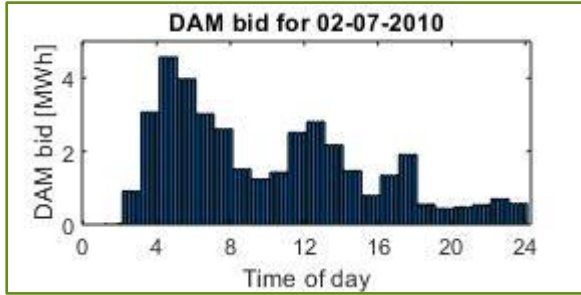


Figure A 24: Optimized DAM bid for Friday 02-07-2010

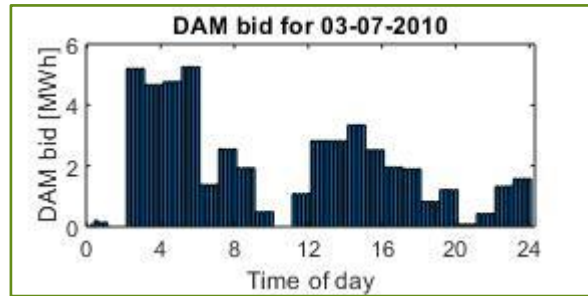


Figure A 25: Optimized DAM bid for Friday 03-07-2010

## Intraday module

With the expected behavior being confirmed by the DAM module results, it is concluded that the module is validated. The intraday module needs no additional validation since it is the same algorithm as the battery capacity optimization model. The difference between the two is that the MPC intraday module optimizes the schedule up to a horizon of 12 hours, whereas the battery capacity optimization model optimizes the schedule and battery capacity for the whole simulation length.