Techno-economical design study for a sustainable power station powered by simultaneity of wind, solar, and an integrated Li-ion battery

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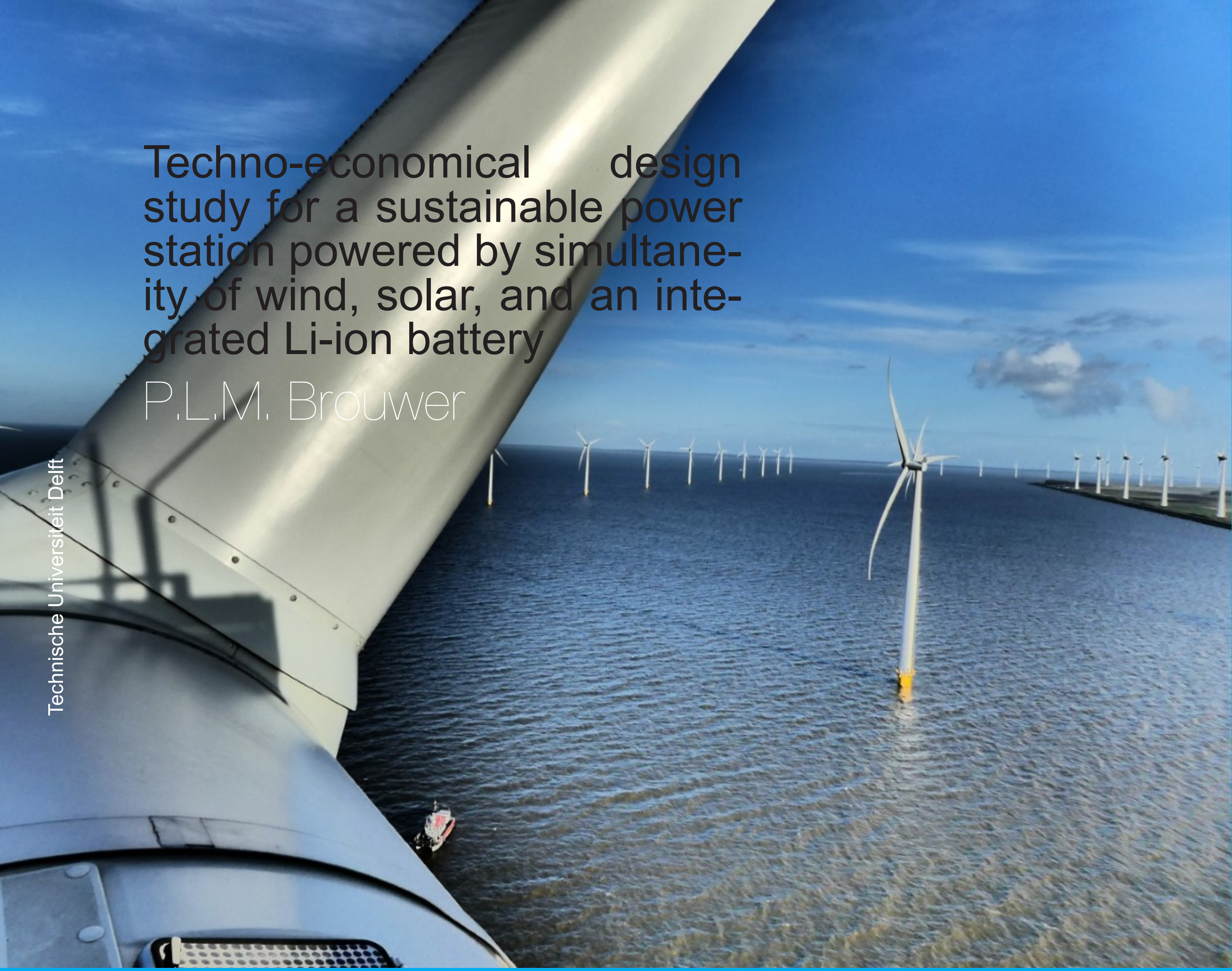

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General Summary

Reason for this research
Our present day society is utterly dependent on electricity. This dependence will only grow as electrification of sectors such as manufacturing, transportation and building heating takes off. Most of the electricity these days comes from conventional plants running on coal and natural gas. Despite that these are reliable and cheap, the disadvantage of emitting greenhouse gases is no longer acceptable. Sustainable alternatives such as solar PV and wind have the highest potential. However, the replacement of conventional power plants by sustainable alternatives is subject to understanding the intermittent and unpredictable behavior of both wind and solar PV and thereby ensuring that generation equals demand at all times. Energy storage technologies allow for separation between generation and supply to the grid. The aforementioned makes the large scale integration of wind and solar PV more difficult. This study lays the foundation for an interconnected system model where solar PV, wind, and battery storage is combined. This study is therefore deliberately different than existing studies focussing on small, already severely contrained systems, such as island systems.

Goal and Method
This research considers the grid connection capacity limitations as an important driver for combining wind, solar PV and grid-connected storage optimal on a single grid connection. Is it possible to design a hybrid system and what would it look like? Is it possible to use grid-connected storage with current prices? To come to an answer to these questions, the simultaneity of both solar PV and wind is studied first. Thereafter, different battery services are identified and have been implemented in a dynamic optimization model with the objective to maximize profit. The first model proposed (Battery Model) is looking for the optimal battery size in MWh when a solar PV farm is connected to an existing onshore wind farm. In the model proposed, all the energy which can be generated must be stored or fed on to the grid. In the second model (Imbalance Model), the value of self-inflicted imbalance is examined and whether the hybrid system is able to be a balance responsible party with current imbalance settlement prices. The third model (Battery PV Model), is looking for the optimal battery size in MWh and the optimal solar PV farm size in MWp. In the third model curtailing a limited amount of the solar PV production is allowed.

Sustainable Power Station
It turns out that it is possible while being self-reliant, using all the potential renewable energy and shifting the generation by arbitrage on the APX market to design a system with an increasing rate of income. The simulations showed that when the combined generation (of both wind and solar PV) during peak availability is higher than the grid connection capacity, the computed battery size increases rapidly, causing a swift decrease in rate of return. This research also shows that with current imbalance settlement prices and battery installation cost minimizing imbalance is less viable than arbitrage on the APX market. The presented results are consistent with how the electricity system currently operates. At last, the results indicate that curtailing 'cheap' solar PV energy with significant overplanting on the existing limiting grid connection is beneficial.

Recommendations for Further Research
In this research some important steps have been taken towards the design for a grid-connected optimal system. The method proposed should be tested with more wind and solar PV generation data. Further research should consider longer periods with real generation data making the results presented more accurate. Further research is also needed on the ability of trading on the FCR market and imbalance market directly. The model needs to be extended by the opportunity to determine what the 'optimal' configuration would be without the already installed wind farm. Finally, the model proposed needs to be studied with different storage systems.

Acknowledgement

This report is the final milestone of my Masters Sustainable Energy Technology at the Delft University of Technology. It really has been a great subject to dedicate my life to for the last 9 months as a student.
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List of Abbreviations

ABL	Atmospheric boundary layer
AC	Alternating current
AEP	Annual Energy Production
APX	Amsterdam power exchange
BESS	Battery Energy Storage System
BRP's	Balance Responsible Parties
CAES	Compressed Air Energy Storage
CAPEX	Capital expenditures (EURO)
CDF	Cumulative distribution function
CET	Central European time
c-Si	Crystalline silicon solar cells
DC	Direct current
DEVEX	Development costs
DOD	Depth of Discharge
ENDEX	European energy derivatives exchange for gas and electricity
ENTSO-E	European Network of Transmission System Operators for Electricity
EPC	engineering, procurement, and construction cost
ESS	Electrical Energy Storage
ESTI	European Solar Test Installation
EV	Electric Vehicles
FCR	Frequency containment reserve
FLEOH	Full Load Equivalent Operating Hours
GA	Genetic Algorithm
GHI	Global Horizontal Irradiance
HRES	Hybrid renewable energy systems
IRENA	International Renewable Energy Agency
IRR	Internal Rate of Return
LCOE	Levelized cost of electricity
LPSP	Loss of power supply probability
MAE	Mean absolute error
MVA	Mega-Volt-Ampere
NWP	Numerical weather prediction
PIF	Profile imbalance factor

PSO	Particle Swarm Optimization
PTU	Program time unit, 15 minute timeframe
PPA	Power Purchase Agreements
PV	Photovoltaics
RES	Renewable Energy Sources
SDE	Stimulation of Sustainable Energy Production (in Dutch: Stimulering Duurzame Energieproductie)
SDE price	Market price plus subsidy
SOC	State of Charge
s.t.	subject to
STC	Standard test conditions
STP	Standard conditions of temperature and pressure
TAC	Total annual cost
TSO	Transmission System Operator
VRB	Vanadium Redox Flow Battery

Nomenclature

A	Area [m^2]
C_B	Capex of Battery system [EUR MW^{-1}]
C_{PV}	Capex of solar PV system [EUR MWp^{-1}]
E_{annual}	Total energy generated over a year [MWh]
E_B	Energy stored in battery [MWh]
E_B^+	upper charging limit
E_{B-}	lower charging limit
eff_{nom}	Nominal efficiency
eff_{rel}	Relative efficiency (compared to efficiency at STC)
G	Global irradiation in the plane of incidence [W m^{-2}]
$K_{battery}$	size of the battery system [MWh]
K_{solar}	optimal size of the solar Photovoltaics (PV) farm [MWp]
$N_{turbines}$	Number of turbines
$P_{imbalance}$	corresponding imbalance timeseries of a chosen windfarm [MW]
P_{max}	Maximum designed power output [MW]
P_{wind}	Power generated by the wind farm [MW]
$\hat{P}_{wind}$	Forecasted Power wind farm [MW]
P_{solar}	Power generated by the solar farm [MW]
P^n_{solar}	Power generated by a 1 MWp solar PV farm [MW]
PV_{out}	Power generated by solar farm (e.g. optimal output) [MW]
T_a	Ambient temperature [°C]
T_m	Module temperature [°C]
U_a	Coefficient describing the effect of the radiation on the module temperature in the Faiman model [W/°C m^2]
U_b	Coefficient describing the cooling by the wind in the Faiman model [W_s/°C m^3]
U_1	The 10m wind speed [m s^{-1}]
U_2	The wind speed at hub height [m s^{-1}]
Z_2	Hub height [m]
Z_1	Measurement height [m]
α	true value of imbalance [EUR/MWh^2]
β	Location specific wind shear component
η_{farm}	Farm efficiency
η_{charge}	Charging efficiency battery system

$\eta_{discharge}$	Discharging efficiency battery system
λ^{+}	Long imbalance price [EUR MWh^{-1}]
λ^{-}	Short imbalance price [EUR MWh^{-1}]
ρ_1	Penalty factor
τ	Tau [time step in hours]

1 Theoretical Background and Literature Review

Development of Renewable Energy
The current society is utterly dependent on the usage of large volumes of controllable power sources. Conventional energy sources always were the cheapest and most obvious source of energy for industrialization and growth. One important liability is that the use of uranium and fossil fuels is finite, producing power generation from these resources is therefore by nature unsustainable. At present, mankind is critically dependent on its energy supply in the form of electricity. Electricity provides heating, cooling, , lighting, communication and transportation. Also, a wide range of industrial processes are depending on electricity. In addition, electricity is making up 40% of the rise in final consumption to 2040 - the same amount of growth oil took the last twenty-five years [1].

Greenhouse Gasses
At this moment, the scientific certainty about the human influence on the increase in anthropogenic Greenhouse gasses, mainly CO_2, increases strongly. The earth is warming up due to human activities and reached the milestone of 1°C in 2017 compared to pre-industrial temperatures and will presumably rise with 0.2°C per decade the coming years (if we keep living in the same way we currently do) [8]. A consequence of the global increased average temperature is that more extreme weather events occur, and ocean and sea water levels are expected to rise and risks with respect to supply of food emerge. Burning fossil fuels is the largest contributor to this increase and thus predominantly responsible for the negative effects on climate, society and nature. In order to comply with the Paris Agreement signed in 2016, to limit global temperature increase to well below 2°C above pre-industrial levels, and to pursue efforts to limit this increase even further to 1.5 °C [9]. In addition, the European Commission has set three ambitious targets for the years 2030 that they agreed upon to [10];

- cut greenhouse gas emissions by 40% (below 1990 levels);
- 27% of the energy consumption to come from Renewable Energy Sources (RES);
- 27% reduction in primary energy use, by improving energy efficiency;

Following this ambitious goal (of climate change), countries are being forced to decarbonise their energy sector. Decarbonisation of the energy sector also means further electrification as most renewable energy sources produce electricity.
Multiple promising RES such as Solar PV, Wave Energy, Tidal Energy, Biomass, Geothermal, Hydro power, and Wind are capable of generating energy without environmental pollution. Nuclear fission also lacks the pollution of greenhouse gas emissions, but instead has the disadvantage of nuclear waste and the development of new installations is a political issue in most countries. Nuclear accidents in Three Mile Island (1979), Chernobyl (1986), and Fukushima (2011) have shown that the environmental impact had far reaching consequences regarding safety and an severe impact on public opinion. For these reasons the acceptance of nuclear fission is very low and not considered as a worthy alternative for fossil fuels. Also, large hydro facilities do not have the drawbacks of fossil fuel-powered generation since it uses sustainable supply of precipitation for power generation. Furthermore, its potential has already been exploited for a large part, especially in developed countries.

Currently, Solar PV and Wind turbines are the most promising and economically viable options [11]. These two promising RES are completely weather dependent for their (potential) output. A second advantage with the introduction of RES is the independency of fossil fuels and a significant increase in the security of energy supply.

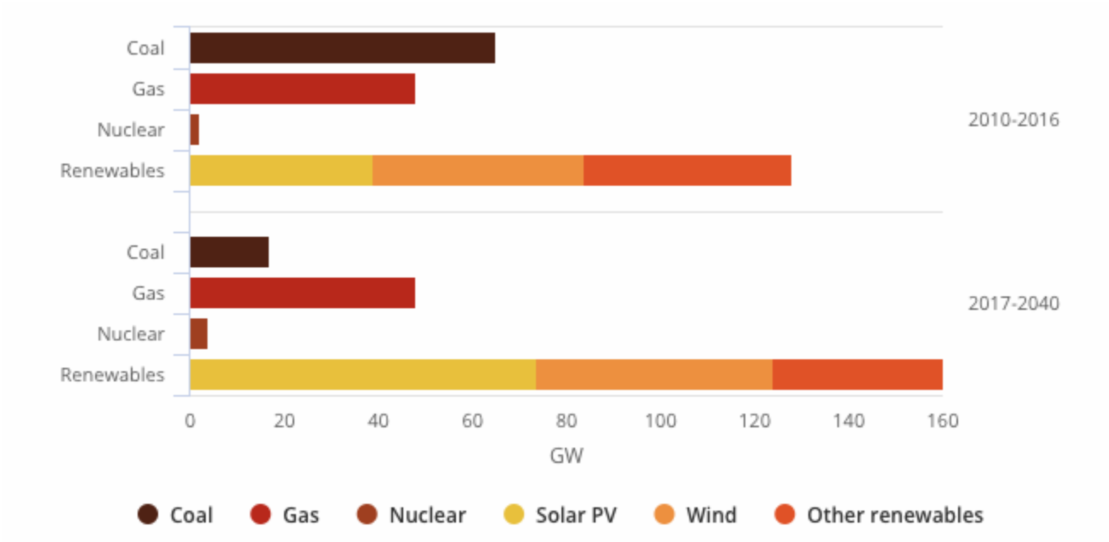


Figure 1: Global average annual net capacity additions by type (source: IEA 2017[1])

When looking at the recent cost reports provided by the International Renewable Energy Agency (IRENA)in 2016 (See Appendix A) one can see that most techniques like Biomass, Geothermal, Hydro, and Onshore Wind are already cheaper or in the same range as fossil fuels. Offshore Wind and Solar PV is in the same cost range as fossil fuels. Despite that these new power generation technologies are competing with fossil fuels regarding costs, the controllability is considered to be a major disadvantage. Since the share of generation capacity by intermittent RES is rapidly growing (Figure 1), the downsides, which arise next to it, are also becoming more important. The current European power systems are built for conventional power plants with well adjustable outputs (dispatchable), Gas Turbines, Coal plants and sustainable fuels (biomass). The integration of wind and solar energy in the existing electricity grid in combination with the electrification of modern society, is resulting in a scarcity of grid connections for the integration of future projects. The absence of available grid connections is already causing deceleration in the development of new wind and solar PV farms. The Dutch power grid is designed in a way that places where the population density is high, the load demand will also be higher compared to sparsely populated areas. Densely populated areas are equipped with a heavier electrical infrastructure. However, the utilization of new wind farms and solar farms is increasingly growing in areas where land is cheap and population density is low. A further increase of electricity generated from renewable energy sources is challenging for the way electricity systems are designed. In various countries with a strong growth in RES, this causes an increasing amount of grid connection capacity limitations, both on the transmission and distribution level.

In rural areas or places where large grid connection are not available, the combined system of wind and solar would become the better solution for a more continuous energy generation than having either technology working alone. Additionally, the total installed capacity can be higher without the instant need for increase of the transmission capacity. Simultaneously, electricity consumption is strongly in correlation with economic growth [12] and electrification is inherent to decarbonisation. Hence, if we save energy by using it more efficiently, still (much) more electricity would be needed.

Apart from scarcity of grid connections, the intermittency in the power production by Solar PV and Wind can cause problems on different time-scales. Ranging from seasonal to 20 milliseconds fluctuations related to maintaining the 50-HZ AC grid frequency.

1.1 Pre-feasibility Assessment for a Sustainable Powerstation

Given that solar and wind power resources will probably constitute major components of the future Dutch and most likely European power system, planning and designing of the future power system requires an in-depth understanding of this intermittency. Both wind and solar output are highly variable, yet, it is commonly known that in summer the monthly mean wind speed is lower than in winter. Also the monthly mean irradiance is higher in summer than in winter.[13] On a daily time scale, the wind power potential at night is significantly lower than during daytime.[14] However, when we look at the Atmospheric boundary layer (ABL) wind speed evolution we see that for high hub heights the wind speed at night can be higher. *Please note that this study is mainly focussed on onshore or subshore windfarms with generally lower hub heights then offshore windfarms.* The variation between day and night is largely due to the fact that temperature differences between the sea surface and the land surface tend to be larger during the day than at night. For the electrical power system and the wind turbine owners it is an advantage that most of the wind energy is produced during daytime instead at night.
Solar irradiance is only available during the day and has its peak value around noon. Looking at the seasonality effect of peak- and average resources, the capacity factor is strongly variating. The capacity factor is the ratio of actual energy output to the output of the solar or wind farm would have produced at their nominal power at all times. The theoretical maximum is therefore equal to 1MWh MWh^{-1}.

$$CF = E_{annual}/(P_{max} * 8760) \tag{1}$$

Where E_{annual} represents the total energy generated over a year, and P_{max} is the maximum designed power output.

Figure 2 shows the seasonality effect of peak- and average resource throughout the year. 24-hour average of wind power and 24-hour average of solar power is normalized to show that their peak generation is for solar in summer and for wind in winter. The combination should in theory result in a more stable output throughout the year.

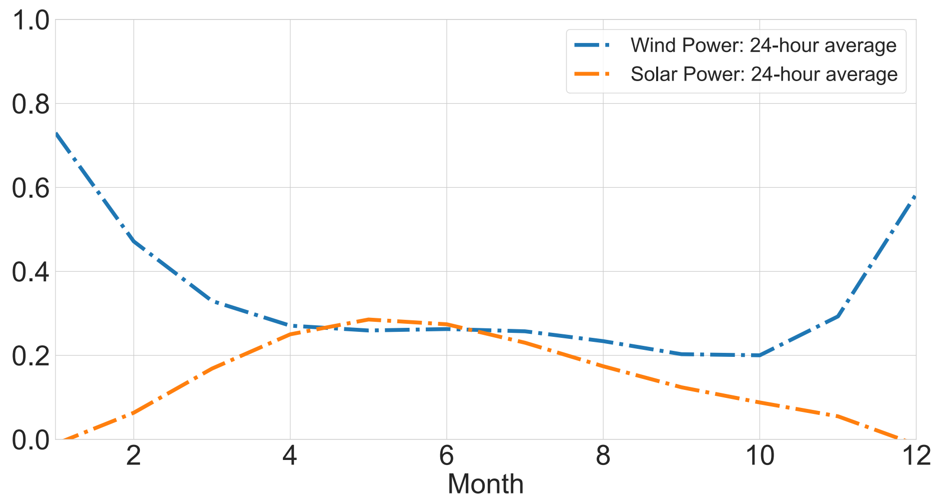


Figure 2: Normalized Solar and Wind Power Potential for a typical onshore location in the Netherlands. Capacity factor on the y-axis. (source: METEOSAT Satellite PVGIS)

In this work, the local complementarity of wind and solar PV energy over the Netherlands and Europe is studied extensively. The variation occurs on different timescales; from seasonal, monthly, daily to minutes/seconds. In section 2.2 the daily, weekly, and seasonal pattern of both wind and solar are described in more detail.

Seasonal and monthly variation can be accommodated by long-term energy storage in the form of pumped hydro or by energy conversion (power-to-fuels, e.g. power-to-hydrogen). For seasonal and monthly variation significant quantities of energy are needed to be stored. These storage facilities or energy carriers do not need the ability for fast charging and discharging. The cost per MWh is more important since larger quantities are needed. Also, the gain is lower since it is used less intensive. For daily basis different solutions are needed. Smaller amounts of energy are needed to be stored, but more often with respect to the seasonally stored energy. For daily and weekly storage herefore alternatives as batteries are more suited for this purpose. Demand side response on the consumption side. together with short-term storage on the generation side will most likely become the potential solution. Variations on the very short time, are currenty captured by reserve generation capacity (i.e. capacity which is able to ramp up or down very fast).
How these different timescale variations can be reduced will be described in section 1.2 (*Balancing Supply & Demand*).

1.2 Balancing Supply & Demand

A conventional grid without the intermittent RES has only to deal with the variable behaviour of the load since conventional sources are more controllable in their output. However, due to the highly variable RES, different challenges occur in terms of balancing supply and demand compared to a power system with conventional generation units. Electricity demands are typically low at night and high during the day [15]. These difficulties can be addressed in multiple ways: Firstly, demand and supply can be shifted over distance (using interconnectors). Secondly, demand and supply can be shifted over time (via storage). Thirdly, demand and supply can be balanced by price incentives.

Interconnectors
The European Council of October 2014 called for all EU Member States to achieve interconnections of at least 10% of their installed electricity production capacity by 2020. This means that each Member State should have cables in place that can transport at least 10% of nationally produced electricity to its neighbouring countries. In 2017 in the communication on strengthening Europe's energy networks the Commission proposed to operationalize to a recommended 15% target [10]. One of the reasons for this requirement is that electricity grids can manage increasing level of renewables better, in particular variable renewable sources like wind and solar. Benefits of cross-border integration, better use of existing interconnectors and investment in new interconnector capacity will increase the flexibility of the European system, therefore it will utilize the advantages of a bigger system. Recent studies have shown that increased interconnection bring substantial benefits to the highly penetrated RES system as a whole [16]. However, the allocation of the costs and benefits of the interconnector between the two parties remains a challenge. Beneficiaries are the consumers and producers in low-cost regions and high-cost regions respectively [16].

Storage
When there is excess energy in one region this can be used in another region. For example, when a region is severly lacking energy, stored energy can be used to fill the gap. Storage can therefore be used at different timescales. Storage in the form of hydropower can be used for longer timescales (seasonal fluctuations). For example, access to hydro dams in Norway or large quantities of relatively predictable solar PV power in Greece, Spain, and Italy. Battery storage is more likely to be used for daily to hourly storage purposes. An additional gain is the negative correlation between wind speeds at locations far away from each other, weather fronts often move across Europe. Denmark for example, exports a surplus of night-time power to Norway; Norway can hereby reduce its hydro use. This indirectly stores the surplus which can be used later by Denmark in the day-time to meet any generation shortfalls. Currently, batteries represent a tiny fraction of grid-scale energy storage overall, making up 3 GWh or 0.1% of pumped storage (2016). Norway alone has 70 TWh of hydro storage capacity. Optimistic price forecasts (performed by

Bloomberg NEF[17]) have shown that the price for energy storage by batteries will decrease by 52 per cent between 2018 and 2030. The price of 1 MWh battery pack was 600k Euro in 2016 and expected to be around 152k Euro in 2030.[17] As mentioned earlier, battery storage as such, is for now unlikely to be viable for time-shifting supply alone.

Price Incentives
The mismatch between supply and demand can also be lowered by creating a price incentive for market operators to stimulate trading mechanisms. Since electrical energy to date cannot be stored in significant amounts, different markets have emerged for the different time scales. Ranging from the long-term (yearly and monthly) via the day-ahead (APX SPOT) and hour-ahead (APX Intraday) has to lead to a closer match of supply and demand until the moment of operation.

1.3 Power Markets

In the past decade the electricity sector has changed a lot. With more to come. With the liberalization of the electricity sector, generation and transmission became decoupled which made it possible for companies to decide where they buy their electricity. Having the ability to buy electricity from multiple parties resulted in a new system. The liberalization has given rise to different energy markets. This change, led to the formation of the European energy derivatives exchange for gas and electricity (ENDEX) and Amsterdam power exchange (APX). This change resulted eventually in more commercial parties entering the market with a profit maximizing objective. Since electrical energy, today, can only be stored in significant amounts at very high costs, numerous markets have emerged operating at different timescales. In this section the different markets considered at which the Electrical Energy Storage (ESS) can act are described.

The first market is the day-ahead market where energy is sold and bought one day in advance. Hence before consumption and generation. The second market is the intraday market, where energy is traded among sellers and buyers up to 5 minutes before consumption. The third market is the imbalance market where grid imbalances on the grid are solved in real-time (15 minutes). Lastly, the Frequency containment reserve (FCR) market is used for imbalances in near real-time up to 15 minutes. Basically there are two parties acting on the electricity markets, the electricity generation companies and the Balance Responsible Parties (BRP's). Both parties are able to buy and sell on the different markets. The BRP's are buying at the different markets to be able to fullfil their responsibility as balancing the amount of electricity produced and sold.

Market	-1y	-1w	-1d	-60min	-15min	-5min	-30s	t=0
Day-ahead			B					
Intraday				B	B	B		
Imbalance					B			
FCR		B[1]	S	S	S	S	S	R
Bilateral	B	B	B	B	B	B	B	B

Figure 3: Table showing the difference in timing for bidding, acting and response time on the different markets considered. Bidding period(B), Stand-by period(S) and Reaction-time (R).

[1]The current FCR market works with week periods in which the offered capacity needs to be fully available during the week. During this week the offered capacity can be solely used by the TSO for frequency purposes. In order to let more parties enter the FCR market the Dutch Transmission System Operator (TSO) proposed to change this into 1 day time slots (summer 2019) to 4 hour time slots at the end of 2020.

1.3.1 Day-ahead Market

At the day-ahead market energy is traded on a daily basis, and sold and bought for the following day. Energy can be bought and sold per hour, and it needs to be consumed within the period it is bought. In reality, it is very difficult to exactly determine the planned consumption. The net difference is then registered as imbalance. This difference will be solved via the imbalance market. In order to stimulate prediction of energy use and consumption as accurately as possible, the BRP's will be charged a penalty in hindsight.

Every day at 12:00 Central European time (CET), producers bid their minimum (marginal costs) selling price and volume for the following day which they call a supply curve. The bids of the consumers are also sorted in decreasing order which they call a demand curve. Intersection of supply and demand will determine the market price. When one misses the deadline this means no energy will be bought or sold by the BRP's for that day. In the Dutch power system, this is done by EPEX (EPEX SPOT SE), the market regulator. The power exchange offers the ability to buy and provides a suitable platform for power suppliers and consumers in France, Germany, UK, the Netherlands, Belgium, Switzerland, Austria, and Luxembourg. In the Netherlands, it is called EPEX Netherlands, formerly APX. The main activity of the exchange bureau is to compare the received generation and load bids, and to calculate the corresponding market price for each hour. Bidding is anonymous. In the Netherlands, the day ahead market is capped with a maximum price of 3000 EURO MWh^{-1}.

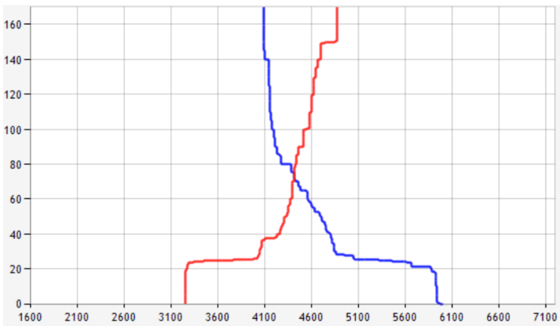
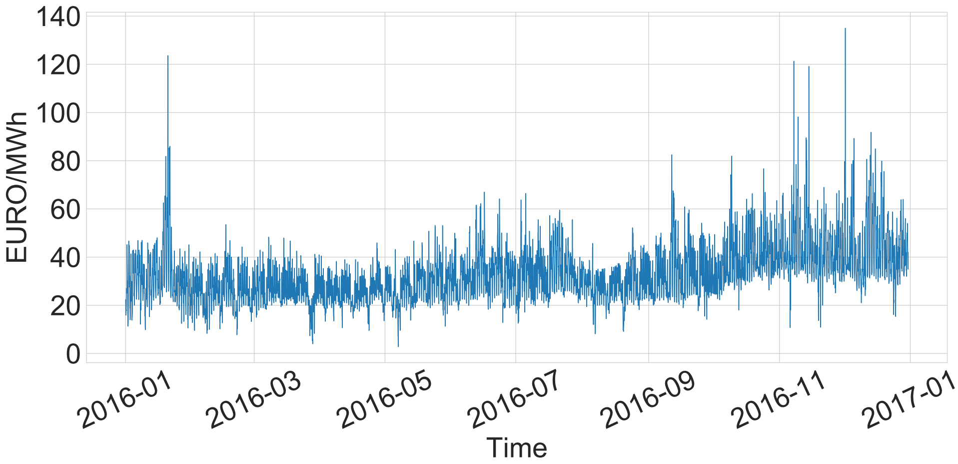
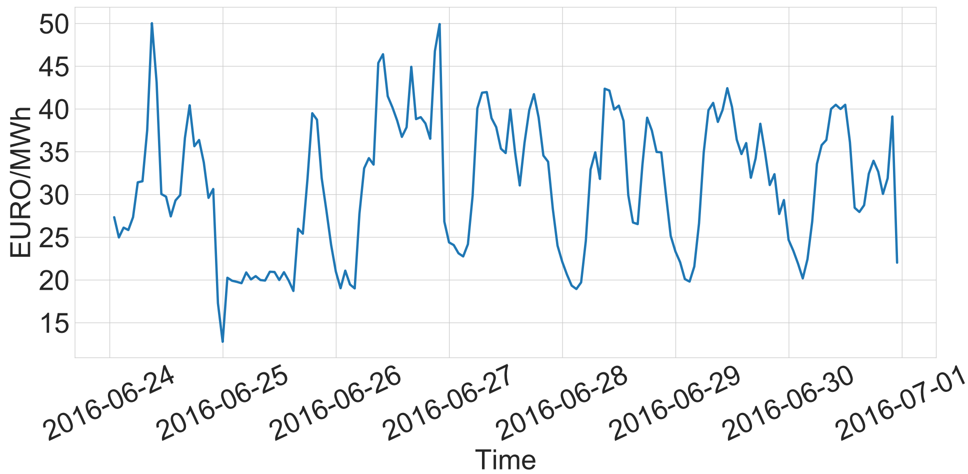


Figure 4: Day Ahead supply and demand curve Market clearing price for 28-08-2019 Hour 21. Where the two curves intersect the market-clearing price is determined, here 71.91 Euro. Market clearing volume 4418 MWh. (source: [2])

In Figure 4 an example is given for a single price market. This means that a single price applies to all the trades within a single time frame. The point where the two curves intersect determines the market price which is 71.91 Euro here.
In Figure 5a the APX price for the period 2016 - 2017 is shown. In the Netherlands the daily traded volume on the day-ahead market is in the order of around 100 GWh per day [2]. In Figure 5b the APX price a summer week in 2016 is given. This Figure illustrates the daily pattern of the day-ahead market with the two typical peaks, one in the morning and one around late afternoon. This is due to the peaks in demand during a day in the Netherlands.



(a) Market prices for 2016 full year



(b) Market prices for a summer week in 2016

Figure 5: Day Ahead (APX) market prices (source: [3])

1.3.2 Intraday Market

Real time transactions happen on the Intraday Market. Quarterly (15 minutes) blocks of energy are traded during the day, untill 5 minutes for consumption. The intraday market is used by BRP's to reduce their self-inflicted imbalance. There is no intraday market price data publicly available. The volume of the intraday market is around 10 GWh [2] and can be considered as a small market.

1.3.3 Imbalance Market

The Dutch TSO, Tennet, is responsible for balancing of the grid, the imbalance market is used to match supply and demand. Given that large volumes of energy to date cannot be stored commercially, the Dutch TSO is continuously matching supply and demand. Imbalances on the grid will result in damage to the national power system and most likely also to electrical devices. The imbalances come mainly from outages, unpredictable energy producers (like RES) and the inaccurate energy use predictions from the demand side. In an ideal system no imbalance

mechanisms would be needed. However, in reality the power flows between supply and demand do not match entirely. Tennet is trying to balance the grid using back-up reserve capacity or by asking producers to ramp down or stop producing. In the current system it is even possible to ask large consumers to decrease their consumption during shortage of supply. The imbalance market is designed in a way that positive contributions are rewarded and negative contributions to the imbalance will be penalized. This mechanism is called "passive contribution", and the BRP's can act freely on this market.
In Figure 6, the imbalance for the last week in June 2018 is shown. The imbalance market is known as a relatively unpredictable market which is very difficult to understand and even more difficult to forecast. The mechanisms behind the positive and negative prices are very complex. For example, when the solar and wind availability is unexpectedly high. Most of the time this will result in a positive imbalance. On the other hand, an increase of wind resources also has an effect on the usage of energy. High wind availability results in a faster cooling of houses and thus a rise in energy consumption for domestic heating. The same applies to solar resources. Forecasting of weather conditions is still very difficult, and not enough understood to match supply and demand accurately. With increasing amounts of variable RES the imbalance will also increase. This mismatch led to an absolute imbalance of 3.1 TWh in Germany and 1.1 TWh in the Netherlands in 2017 [3]. There is no maximum price specified by the BRP's. More information about forecasting of RES will be given in section 2.5.

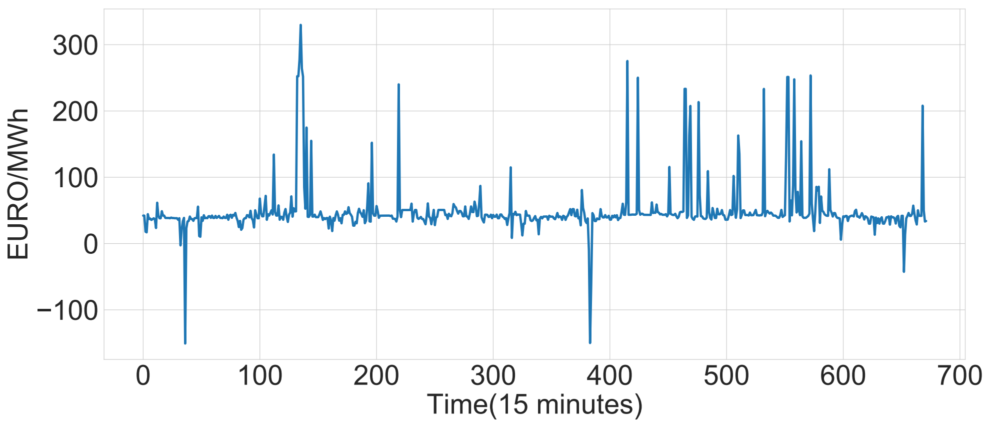


Figure 6: Imbalance Price from 24-06-2018 00:00-00:15 untill 30-06-2018 23:45-24:00. (source: [3])

1.3.4 Frequency Containment Reserve Market

In entire Europe we agreed to keep the grid at 50 Herz as the standard. Because of simplicity for calculation it is chosen to use a multiple of 10 (metric system). In order to ensure a stable and safe grid state the load and the power generation have to be balanced at any time. In the continent Europe the high-voltage grid is maintained at 50 Hertz by matching demand and supply. In case the balance is not retained, the grid frequency is greater than 50 Hertz and there is an excess of energy production. When the frequency is lower than 50 Hertz there is a shortage of supply. The electric power system requires a steady balance between supply and demand to maintain nominal grid frequency. The increase in electricity production from wind turbines and solar PV panels results in an increase in the imbalance of the electricity grid. The forecast error for mainly wind capacity and solar capacity is substantially higher than conventional plants.

In Figure 7 the average auction prices for the FCR market are shown. The total price and volumes can be obtained from European Network of Transmission System Operators for Electricity (ENTSO-E) [3]. According to market experts (June 2019), a week of competing at the FCR market counts as roughly 7 cycles. As can be seen the prices for a MW of around 2500 Euro this is a high price compared to the other markets. In the Netherlands current roll out of large BESS is mainly financed on this source of income. With prices around 2500 Euro per MW this is currently the market where the highest gain is obtained per battery cycle.

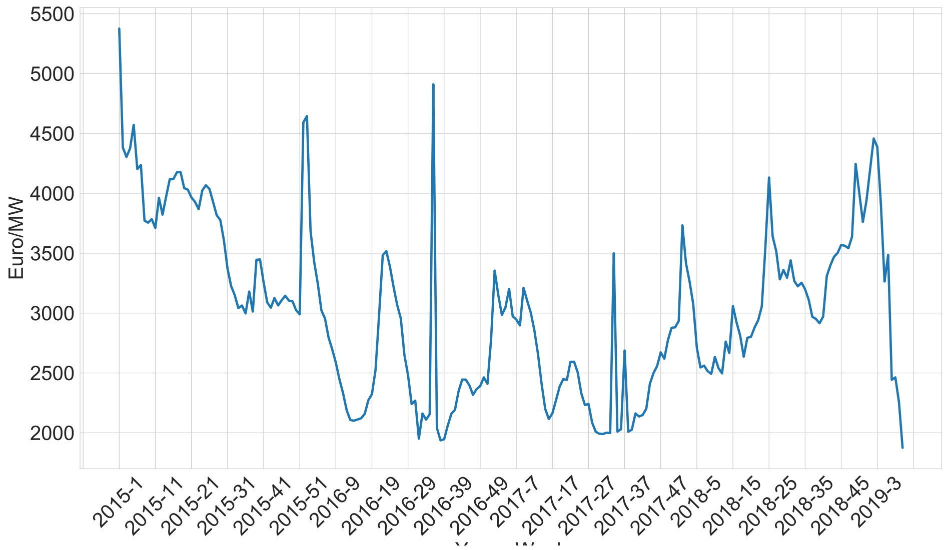


Figure 7: Average Auction Price Primary Reserve (FCR) - 2019YTD. (source: ENTSO-E)

In order to operate with a battery at the FCR market the European code and the Dutch System code have stringent requirements where the FCR units have to comply with. The minimal volume to act on the FCR is 1 MW and increases with a step size of 0.1MW. The FCR market differs a lot with the other market where energy is offered instead of capacity. Hence, prices are given per MW instead of per MWh. The most important technical requirements are determined by the TSO and are listed below:

- Frequency measurement accuracy of 10 mHz;
- Full activation of FCR at a deviation of 200 mHz;
- 100 % availability;
- Activation is proportional to the measured frequency deviation;
- Start-up speed of 30 seconds for the allocated volume;
- The minimum lot size to bid is 1MW symmetrically in upward and downward direction for a period of one week;

1.3.5 Bilateral Contracts

However, the largest volume of produced electricity is traded bilaterally. Large producers sell contracts for delivery directly to large consumers. Pricing of these bilateral contracts are usually confidential and approximately 85% of all electricity produced is sold via these agreements. For the large consumers the upside is risk reduction regarding power price volatility and for the large producers the upside has to do with a better understanding of demand patterns.

1.3.6 Arbitrage

In economics and finance, arbitrage means the possible advantage of a price difference between two or more markets. In the debate on what role energy storage can play in the current contemporary energy markets, arbitrage is one of the many ways for a storage system to be cost

effective. Despite the fact that such battery systems can play an important role in avoidance of costly interconnecting infrastructure and emission reduction[18], investment remains limited. Arbitrage in energy storage refers to the application of energy trading mechanisms within the electricity market environment, where buying electricity from the grid at low price and sell it back to the grid at a meaningfully higher price; take advantage of the spot market spreads.
The difference between off-peak and peak demand results in a price difference that could theoretically produce value, considering the energy conversion losses during this storage operation. Previous studies have shown that the value of this arbitrage was not sufficient in itself to support energy storage investments.[19, 20] These studies concluded that; Along with the high cost of storage systems and the current Western electricity prices and limiting price variations this is not sufficient to be financially viable.

A fast, and very conservative simple calculation shows that the price difference for arbitrage with a CAPEX of 450K Euro MWh^{-1} per cycle needs to be at around 45 EURO (On the assumption that a standard Li-ion battery has a lifetime of around >5000 cycles. By using a 1MW $1MWh^{-1}$ battery a full cycle is from fully discharged to full to discharged again. Therefore, 2 MWh times the amount of cycles comes to 10k MWh. Starting with a CAPEX of 450K Euro divided by 10 000MWh means a Levelized cost of electricity (LCOE) of 45 Euro MWh^{-1}. Experts from Super-B and Alfen (April 2019) confirmed that the cost per MW and per MWh are quite similar. Only for large battery systems the cost for a MWh installed is around 430K EURO. The price difference with arbitrage needs to be therefore at least in this order to be financially interesting.

1.4 Battery Energy Storage System

In this section, the different timescales and purposes of the storage system are considered. Energy storage assists in the separation between the generation of power and the supply of electrical power to the grid. This is predominantly done by transferring electrical energy by conversion into another form of energy, which can be either electrical, (electro-)chemical, thermal or mechanical energy.

Due to the growing need of energy storage systems, a lot of development took place for new technologies. Judging from the amount of published studies, the interest in energy storage has grown very fast in the recent years. Although there are many energy storage techniques available and considered to be a viable asset in the energy power systems, some technologies as Lithium air and Flow batteries are still undergoing development before they are ready to acquire a spot in the current market. Lithium air batteries are known for their high energy density. A lithium air battery consists of a solid lithium electrode, an electrolyte around the electrode, and an ambient air electrode with oxygen. Unfortunately efficiency is still limited by incomplete discharge at the cathode, charging overpotential is greater than discharge overpotential, and component stability is still not adequate.[21] Flow batteries (Vanadium Redox Flow Battery (VRB)) on the other hand, are a special type of batteries, which store at least one of its liquid electrolytes in a storage tank that flows through the reactor to store and create electricity. Typical advantages are that the Depth of Discharge (DOD) can be ignored and self-discharging is negligible. Disadvantages are their low energy density and low charge and discharge rates. The latter excludes this storage technology from acting on the FCR market.
In Figure 8, a comparison study is shown where the power rating is plotted against the rated energy capacity. The variations in discharge time at the rated power is shown in the range from seconds to months. Please note that the marked data is for storage facilities in operation at the end of 2016 and the ones with a star under construction. Moreover, that lithium air is not present in Figure 8 because it is not yet used on a large scale.

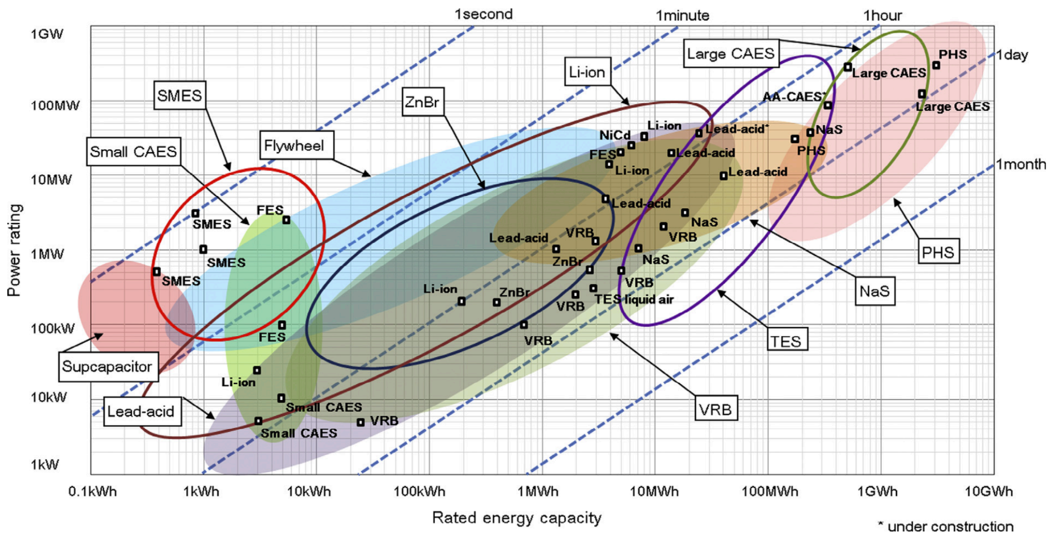


Figure 8: Comparison of power rating versus rated energy capacity.[4]

It is clear that no energy storage technology can meet all power system applications. In terms of power and energy rating the lithium-ion battery is one of the most promising ESS system. The current utility scale Lithium-ion batteries outperform on almost every aspect traditional batteries. The most vital characteristics that lithium-ion batteries have are roundtrip efficiencies up to above 95%, long life cycle >5000 cycles at 80% DOD, fast charge and discharging, and a high power density.[22]

Consequently they are considered the most promising energy storage for short-term (daily to weekly fluctuations) and are preferred over traditional batteries as lead-acid, nickel based batteries, and sodium-nickel-chloride batteries.
Recent studies and press releases lately have shown that the batteries in hybrid power systems and high-power battery applications as Electric Vehicles (EV) so far have been deep cycle batteries such as Lithium ion.[23] The input details for the model proposed like capacity, efficiency, cost, energy density, and operating life cycle will be discussed in section 2.7.

Long Term Storage
To match the seasonal differences between supply and demand, large scale energy storage methods such as pumped hydro, energy conversion in the form of electrolysis (hydrogen generation) or large Compressed Air Energy Storage (CAES) is required. These techniques are able to store large quantities of energy for a significant duration with a low self-discharge or in most cases without self-discharge. Power density and cycle efficiency are less important, also ramp-up and ramp-down time is less important. As this study is focusing on the daily to weekly fluctuations in the wind and solar availability these are not taken into consideration.

1.5 Storage Business Case

Before utility scale BESS will be constructed to a great extent and assist in achieving the goals set by the European Commission, the advantages needs to be analyzed thoroughly. Despite the unarguable benefits for storage facilities, research in this region is needed to create comfort among stakeholders and incentivize the future roll out.
Energy storage is a type of generation unit. In liberalized markets, investment in generation capacity is determined and done by commercial parties and investment in energy storage depends on the business case for such an investment. That business case depends on the income generated by the generation unit: the volume produced and the price at which that volume is sold. In an interconnected system, the unit is competing on an open market and the price is therefore difficult to determine for longer periods of time (i.e. 5-15 years ahead, typical payback periods).
Compared to conventional generation capacity, the business case of storage is more complicated because the 'fuel cost' is in fact more uncertain (at what price is the energy bought and stored) and also the income is more uncertain (what volumes are bought and sold, and at what price). Compare this to conventional generation, where fuel costs are hedged by long-term fuel contracts and long-term Power Purchase Agreements (PPA) for fixed volumes, or offshore wind, where the fuel cost is zero and the income is known quite well based on yield calculations, government guaranteed prices EUR MWh^{-1} as well as long-term PPAs. Finally, it can be noted that energy storage also has more competition than conventional generation: other sources of flexibility like interconnection capacity to hydro-based systems (Norway) or demand-side management impact storage more, because the price of not only the power sold but also the power bought is changed, impacting the business case of storage on both sides! History shows that extension of the high-voltage transmission system can take up to 10 years before fully operational. These extreme slow extension of the (high voltage) electricity grid will delay the build out of fossil fuel free generation plants significantly.
What this all means, is that for any business case for storage, there is a fundamental need to determine both the volume and the price of the energy bought and sold. Different markets exist for different volumes each with their own price and market opportunities.

Sources of Income

In a combination study where the introduction of coupling a BESS with both solar and a wind farm on a single grid connection will be connected several benefits can be obtained. These benefits, could possibly, next to facilitate in the growth of the renewable energy sector be seen as an important source of income for the storage facility in the total system as a whole. Table 1, gives an overview of the services which can be full filled with a battery. Each battery purpose is at its own valuable. For every service a price range and market size is stated. The prices and sizes are determined by literature review [7, 3, 2] and interviews with market experts. By sharing a grid connection a large share of the CAPEX of a new wind, solar farm or BESS can be split making more new projects viable.

Battery Services & Potential Market Volume	Description
1. FCR Market Frequency control (± 96 MW) price range: 2000-4000 Euro MW^{-1} w^{-1}	In periods when solar and wind energy cannot be maximum the (remaining) battery capacity is used to bid on the FCR market.
2. Imbalance Market Prevention of imbalance (±300MW) price range: 80 en 120k Euro MW^{-1} y^{-1}.	The difference between the forecasted energy production (nominal power) and the actual production will be lowered by using the battery.
3. Day-ahead Market Storage of excess energy (≥ GWhs) price range: 0-200 Euro MWh^{-1}	When the total energy produced is higher than the export limit of the cable (cable capacity) this energy will be stored in the battery and can be sold at a later stage.
4. Self-consumption (±0.1% install. capac.) price range: 40-60 Euro MWh^{-1}	During Dunkelflaute(no wind nor solar energy generation) the energy needed for control of the wind farm, solar farm, and battery will come solely from the battery. Hereby avoiding paying for peak consumption tariffs.
5. Grid cost reductions price range: highly dependent on location and size of installation	Sharing of a grid connection (Wind, Solar, and BESS) lowers the cost for connecting to the national transmission grid.

Table 1: Overview of the different battery services considered with explanation. July 2019. Source[7]

1.6 Problem Statement

Storage and conversion of energy is key for the introduction of high RES penetration. Storage needs to be identified as a crucial component of RES generation capacity. Currently, there is a lot of development in RES, however minimal development in storage (Hydro already utilized). The business case for battery storage is currently quite uncertain and therefore one of the reasons why the roll out of storage is lagging behind. This is due to the high upfront investment cost, legislative barriers, and the sparse knowledge about batteries on the long term. The EU regulatory framework is still not ready to accommodate new flexible solutions. Similarly, interconnected system and low electricity prices do not promote the high investment costs. For this, real price data and limiting electrical infrastructure needs to be studied. The optimal configuration of both solar and wind needs to be studied. The availability of both solar and wind during the year as well as daily patterns should be studied and evaluated in greater depth. When and how often are wind and solar availability at its maximum. This combination can then be coupled to the optimal BESS size. Subsequently Current research has been done in constrained (small) systems, where these are completely different from large interconnected systems. Similarly, real market price data and grid connection capacity limitations are often excluded. The business case for storage in interconnected systems is depending on different services, volumes, and prices. BESS is capable for different services (Self-consumption and avoidance of peak-consumption, frequency control, Emergency Power, prevention of imbalance, grid cost reduction, and storage of excess energy). The question is, how can BESS optimally be modelled in an interconnected system while maintaining reliable operation and offer capacity to the different battery services.

1.7 Previous Optimization Studies

There have been many different studies looking into the combination with solar and or wind coupled to a storage system. The studies listed in Table 2 has different aims, regions of interest and methodological approaches. The first step after pre-feasibility analysis and selection of the suitable storage system is to accurately asses the size of individual components that can satisfy the predetermined constraints. In this section different studies looking in to these issues are shown. Table 2, gives an overview of recent studies looking into sizing and modelling of Hybrid renewable energy systems (HRES). Special attention is given to details as Method/Technique, input data and the outcomes provided.

Generally there are two frequently used approaches to determine the optimal sizing in terms of a technical analysis and an economical analysis. The first method is using a method in which the right size is determined for the renewable energy system components by minimizing the system cost while maintaining system reliability. The second method uses a Loss of power supply probability (LPSP) technique. The LPSP is the probability that a net deficit power supply results when the HRES is not satisfying the load demand. This method is mainly used for stand alone systems (off-grid hybrid systems) since the loss of power here is inevitable. Most studies however, do aim for the configuration in which the lowest overall system cost is obtained or the lowest levelized cost of electricity [24].

Rahman and Chedid [25] gives the concept of the optimal design of a hybrid solar-wind system. Both grid connected and autonomous is reviewed. They are using linear programming techniques to minimize the the cost of electricity while fullfilling the load requirements. Reliability and environmental factors are considered in the design and operation phase. In a study performed in 2015, [26] a multifarious Particle Swarm Optimization (PSO) is used to determine the optimal size of a PV/wind/battery hybrid system for different locations in Iran. PSO is a computational method that finds the optimum of a problem by iteratively trying to improve a candidate solution with regard to a given problem. The sizing is done on the basis of minimum Total annual cost (TAC). The climate differs from the one in this study due to the striking amount of solar radiation and low wind speeds. A similar methodology is used in [27, 28] an optimal design is proposed in which the annual cost of the system is minimized while satisfying the loss of power supply probability optimal at all times. In [27] the 20-year total system cost is equal to the sum of the respective components capital and maintenance costs, the method uses a genetic algorithm, which have the ability to attain the global optimum with relative computational simplicity. A genetic algorithm is a random-based classical evolutionary algorithm. The optimum is found by randomly making changes to find the best solution. The case study is for a power generation system which supplies a household and is therefore a small system which can be considered as a microgrid.

In a study performed in 2008 [29], a triple objective (multi-objective) design of isolated hybrid systems minimizing the total cost throughout the life of installation, greenhouse gas emissions and unmet load. A case study is provided in which a complex pv/wind/diesel/hydrogen/battery system is designed. Seasonal variation of PV and Wind power generation is studied by Markvart (1996) [30], where the problem of optimal sizing of the PV and Wind power sources in a hybrid configuration system is also formulated as minimize total system cost. The cost per unit area and the energy production at day t per unit area (kWh/m^2) is taken into account here. The battery size is not optimized in this method and the load needs to be satisfied at any moment. The model uses meteorological data for a given location. A strong focus within this study is on the summer-winter analysis, using mean monthly data as an input.

In a study performed in 2008 by Diaf et al. [31] a design and techno-economical optimization for hybrid PV and Wind system under various meteorological conditions is proposed. The primary objective in this study is to estimate the appropriate dimensions of a stand-alone Hybrid system that guarantee the energy autonomy of a typical remote consumer with the lowest LCOE. The system is designed and modelled for five different sites in Corsica with solar insolation levels of around 4.5 kWh/m^2 and with annual wind speeds varying from 3.1 to 7.1 m/s. The proposed design is also optimized for energy autonomy of a typical remote consumer.

Author/year	Objective	Method/Technique and Input Data	Conclusion
Maleki/Mehran [26] (2015)	Optimal sizing of a PV, Wind, and Battery hybrid system. High reliability and minimum production total costs over the life of the system.	Multifarious particle swarm optimization. Meteolorological data and real time information(hourly) is used as an input.	(1)Derived result with particle swarm optimization with constriction factor is more favourable than others.(2)Economic modelling showed that the geographical situation of Iran (striking amount of solar radiation and low wind speeds), hybrid systems (PV-Battery) are suitable for most areas in the country. But if there is a good wind speed at some locations the PV-Wind-Battery hybrid system can be used.
Ai/Yang[32] (2014)	Computer aided design of solar PV/Wind hybrid system.	Loss of power supply/loss of power probability.	(1)Developed complete sets of mathematical formulation for optimum sizing of solar PV/Wind hybrid system. (2)Performance of PV-Wind system is studied using practical load data.
R. Belfkira et al. [33] (2011)	Optimal sizing study of hybrid wind/PV/diesel power generation unit.	A deterministic algorithm is used to find the optimal number and type of units ensuring that the total cost of the system is minimized while guaranteeing the availability of the energy. Hourly real resource data for periods of 6 months is used.	Obtained results show clearly the great impact of the site energetic potential (wind and solar radiation) as well as the load profile on the optimal hybrid system constitution (numbers of wind turbines, of PV panels and of batteries) and the related cost of the hybrid system.
S. Diaf et al. [31] (2008)	Design and techno-economical optimization for hybrid PV/wind system under various meteorological conditions.	By looking for the lowest levelised cost of energy. Input data is unknown.	At all locations, the optimal hybrid PV/wind system, that guarantees a zero LPSP, products a high energy surplus which can reach 75% of the energy production. Therefore, the use of a third controllable energy source as a back-up electricity source (i.e., conventional generator) can reduce the energy surplus while maintaining the LCE at minimum value.

Author/year	Objective	Method/Technique and Input Data	Conclusion
Yang/Zhou [34] (2007)	Optimal sizing method for stand-alone hybrid solar–wind system.	GA with loss of power supply probability and minimizing annualized cost of system. Long term weather data is used as input data.	(1)With relative computational simplicity to conventional optimization methods a optimum design is found. (2)Decision variables included in the optimization process are the PV module number, wind turbine number and battery number.
Kellog/Nehrir [35] (1998)	Generation unit sizing and cost analysis for PV/wind system.	Numerical algorithm. Hourly meteolorological data is used as input data.	(1)Optimum generation capability and storage required is determined for a stand-alone, wind, PV, and hybrid wind PV system for an experimental site. Condition is that load must always met.(2)Hybrid combination is more reliable.
S.Rahman/R.Chedid [25] (1997)	Optimal design of a hybrid design of a hybrid solar-wind power system.	Linear programming Computer aided design (CAD) tool. Hourly load and resource data is used.	(1)Reducing the average production cost of electricity while meeting the load. (2)Environmental factors are considered both for the operation and design phases.
Markvart [30] (1997)	Procedure is described that determines the size of the PV array and Wind turbine in a hybrid system.	Graphical construction. Meteorological data.	(1)For a range of costs of the solar and wind energy systems, the hybrid represents the most cost-effective solution. (2) hybrid system is cheaper since the energy generated can be matched more closely to the load.

Table 2: Summary of modelling methods for optimization solar and wind combination studies

The above-mentioned studies are a good estimation of how hybrid systems can be modelled in small remote areas or in places with high price fluctuations in the electricity price. In this study a system is designed which is connected to the national grid which makes it completely different. Furthermore, Western (European) countries are completely different from the locations summarized in Table 2. In the Netherlands for example, the average power usage per capita (watts per person) is considerably higher than island or remote areas and price fluctuations in the electricity price are also much lower [36]. The room for taking advantage of price fluctuations (Arbitrage, see section 1.3.6) on the electricity markets is therefore also smaller. The cost of electricity is also much lower because of the interconnected transmission network of Northern Europe. For a country as Denmark the total share of renewable energy sources lies around the 42% in 2020 whereby Denmark will have met, and exceeded, its EU obligation for a 30% renewables share by 2020.[37] Yet there is no storage capacity. The Danish electricity system is strongly connected to Norway which has pumped hydro storage potential which can be used for balancing purposes and seasonal fluctuations. However not every country can make use of the Hydro storage capacity of Norway. Other countries have to facilitate their own storage needs.

Renewable Energy Penetration

Before, 100% RES systems were studied at the European and Global level, both without storage and transmission networks. The system required 100% excess energy for Europe. For the Global level it was almost 60%. Furthermore introduction of optimal transmission lines could reduce excess generation capacity to 30% and 45% respectively. A study by Aboumahboub et al. [38] has shown that the introduction of a small storage fraction led to large benefits. The addition of storage facilities was much cheaper than several transmission lines of 100 GW range (these effects were achieved with storage being used for intraday balancing rather than seasonal). Research indicates that the role of storage becomes more relevant for high RES penetration. Below 30% penetration curtailing the excess energy is usually the most cost effective solution. Wind and Solar curtailment is when the system operator cuts the amount of generation that can be sold to the grid for a specified amount of time, mainly caused by one of the two following factors: mismatch between supply and demand (voluntary curtailment, it is more cost effective to stop generating since the electricity price is for example negative) or the transmission system is incapable of accommodating the full dispatch of both wind and or solar power (involuntary curtailment). This has mainly to do with that the number of hours that there is a surplus is not sufficient to justify investment in storage facilities. However, when one wants to achieve fraction up to 80% or even higher storage plays an important role and reduces the overall system cost (compared to a system without storage). The addition of extra generation capacity has diminishing marginal added value when it comes to daily fluctuations.[38]

1.8 Research Objective(s) & Approach

As shown in the preceding sections the integration of large intermittent RES results in a wide range of difficulties. The system wide aspects of integration become more and more important since the scarcity of grid connections is rising.

Based on the background and the related above mentioned technologies, the study aims to design a 100% sustainable power station powered by simultaneity of wind, solar, and an integrated Li-ion battery all at one grid connection. A better understanding of both solar and wind availability on multiple timescales is needed. The proposed methodology intends to avoid over- and under-sizing for a combined power system.

This report will focus on the different steps considered in designing a specific 100% sustainable power station instead of a scenario study or review of different optimization techniques.

What is a sustainable power station?
The sustainable power station is a design in which solar, wind and a BESS system are combined where no curtailment is allowed and which is fully self-supporting. The design makes optimal usage of the pre-existing electrical infrastructure. Additionally the imbalance caused by the wind farm is minimized.

The following research assumptions are taken in this study; Export capacity is fixed (limiting electrical infrastructure) and the size and power production profile of the wind farm is set.

The following research objectives will be discussed in this report:

- Main objective is to develop a methodology for the optimal design of wind power, solar PV power, and storage at a single (limiting) grid connection.
- The first sub-objective is to correctly simulate the wind and solar power output over time.
- The second sub-objective is to analyze and investigate the simultaneity of solar and wind power production on a limiting electrical infrastructure. Additionally, real electricity prices are included.
- The third sub-objective is to write a model (Battery Model) that determines how much storage capacity is needed for a given location to be self-supporting (i.e the self consumption will not be supplied by the grid and thus needs to be entirely generated by the combination of solar power and wind power or extracted from the battery).
- The fourth sub-objective is to write a model (Imbalance Model) that ensures a more reliable generation profile. The battery will discharge at periods that the generation is lower than the forecasted power, and will charge in times that the generation is higher than forecasted. This should result in significantly less imbalance caused (difference between generation forecast and real production).
- The fifth sub-objective is to write a model (Battery PV Model) that is able to determine the optimal solar PV farm size and BESS size. Here, curtailing solar PV power is allowed.
- The sixth sub-objective is an application of the three models proposed on a representative case study. Also assess each battery service of how these can add value design for a sustainable power station.

Approach
The approach of this research is to build the model step by step. First the time series with wind speed data and solar irradiance values will be imported and converted to power profiles. This is done using literature research and interviews with market experts on wind speed and wind-power modelling. Secondly, the simultaneity for solar and wind power production will be analyzed. Long-term data sets for wind and solar availability will be analyzed to obtain more

insight in the daily and seasonal fluctuations. Thirdly, different models will be build to meet the sub-objectives (3,4 & 5). Fourth, each battery service will be qualified in terms of value and market size. Subsequently, there will be determined which services can be combined and how these could possibly help to strengthen the business case for large scale integrated BESS. Fifth, the different sub-models will be combined and used for a representative case study.

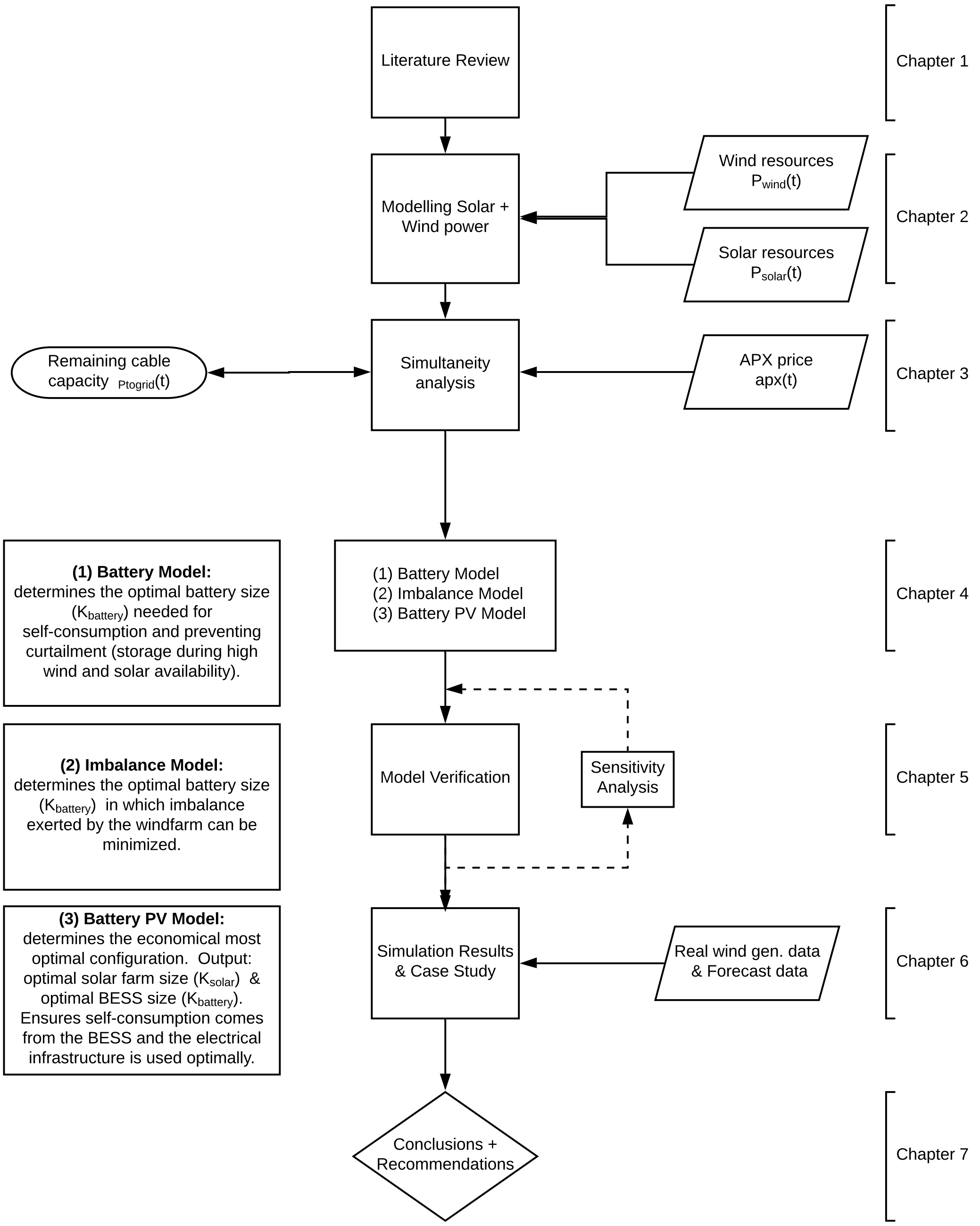


Figure 9: Research work flowchart.

Present Study, Difference From Existing Work
This present study differs from previous studies in hybrid systems in several key aspects; Firstly the system and methodology proposed is designed for a sustainable power system connected to the future European power system instead of an optimal design for a small remote area. Secondly, we are looking at a representative location in the Netherlands with real price data of contemporary markets. Here, the developed methodology is designed for the future Dutch power system where price differences are low and more RES will enter the market. The studies summarized in section 1.7 are designed for mainly remote areas in which they have to compete with diesel generators and or high electricity prices. Hereby showing its importance and potential to neighbouring countries acting on the same markets and receiving comparable solar and wind resources throughout the year. The case studies summarized in Table 2 are often modelled and designed for places with very high solar insolation levels as Corsica and Iran [26, 31].

The onshore location used in the case study, is one of the numerous wind farms where the export capacity is not used optimal. Thirdly, the constraints of designing this power station without curtailing both the solar PV and wind farm component at all times is new. Hereby maximizing the reduction in Greenhouse gasses. Fourthly, using a part of the battery to fulfill the forecasted generation and to limit the occurrence of imbalance. Finally, to be fully self-sustaining is not earlier demonstrated in a grid connected hybrid system. The optimization is done on the basis of hours to days. Not on a yearly basis.

1.9 Outline of the report

This report aims to provide a comprehensive overview of the work performed in designing a sustainable power plant. This research is divided into several chapters and each of the chapters provide insight about certain aspect of the thesis. In order to meet the research objectives this study is structured as below:

Chapter (2) introduces the reader to what input data sources are used and the resolution. All the assumptions are explained and the certainty of the used data sets have been validated. Furthermore this chapter provides insight into the daily and seasonal solar PV and wind power output fluctuations. The method how both wind and solar resources are translated to power output is explained. Subsequently, the concept of imbalance is clarified. At last, the specifics and characteristics of the BESS are given.
Chapter (3) the concept of curtailment is explained and the peak power production of both solar and wind is analyzed. This must be applied to obtain insights in the length and size of the periods in which the electrical infrastructure is limiting. Aforementioned is needed to get an indication about the storage capacity needed.
Chapter (4) describes the optimization method used and the mathematical relations used as an input in the optimization software. Additionally, the constraints, input parameters, objective functions and different sub-models are discussed.
Chapter (5) the model is verificated analytically to show that it is modelled in the right way.
Chapter (6) introduces the reader to the remainder of the simulation results and is a chapter in which the results are presented in terms of a representative case study.
Chapter (7) is a chapter where conclusions with respect to the research questions are shown. Based on the predetermined limitations and constraints, recommendations for future research are presented.

2 Modelling Wind, Solar PV, & Battery System

2.1 Raw Input data

In this study, wind and solar data sets are analyzed here at a National and regional scale. Before going into the details of these data, it is important to realize what the intended applications are: use as input for simulations of a technical design study for a combined solar, wind, and storage system. Simulations help to determine the optimal sizing of the BESS and the solar PV farm. Since these simulations comprise time-scales up to years, resolution of 1 hour data seems reasonable.

As summarized in Table 2, existing studies use also hourly data points. The study carried out by Markvart [30] uses even a similar meteorological data set as input.

The used input data is obtained from PVGIS[5] and publicly available. PVGIS uses satellite data from the eastern METEOSAT satellite. [39] The typical data sets used in this study are for a typical onshore location in the Netherlands in Flevoland. The time series have been used to hind cast the solar and wind output over time for a 10 year period (2007-2017). Note that the value of this data sets is in the completeness in which 10m wind speeds, solar insolation values and temperature is present. METEOSAT data covers Africa, Europe and Asia up to 60°N with an image resolution of only a few kilometers.

In this study winter/summer savings have not been taken into account. All time stamps used in PVGIS are referred to UTC. UTC time differs 2 hours with local time during the summer in the Netherlands (UTC+2) and 1 hour in winter (UTC+1).

Wind Speed

The 10-m hourly wind speeds available in the METEOSAT satellite are used for the calculation of the wind energy potential and variability. The wind speed at hub height needed has been obtained by a vertical extrapolation. In Appendix B, the simulated wind speeds have been validated with real generation data and wind measurements of a typical onshore location in the Netherlands. The vertical extrapolation results in slightly lower generation than real measurements show.

Wind availability is really fluctuating over the years. Windex [40] provided a long-term norm for the wind speeds in the years 1996-2015. Windex [40], by Windunie demonstrates that 2011 and 2006 are typical wind years which can be used for doing an analysis of multiple years. However the variability is too significant to conclude on the basis of one year data. However, it does provide a good indication in terms of energy quantity with respect to an average wind year.
When the model starts to minimize the imbalance the 10m wind speed wind data is replaced by real production data obtained from the wind farm owner. This data set contains for every Program time unit, 15 minute timeframe (PTU) a 24-hour forecast, the power delivered to the farm, and the power fed into the grid. Given that the Imbalance Model is able to minimize the imbalance, the Imbalance Model uses real imbalance values in combination with production data instead of the 10m wind speed as input.

Solar Irradiance

The solar radiation data sets have been validated to look at the degree of uncertainty. Multiple scientific papers have presented a comparison from the satellite data with ground station measurements from the Baseline Surface Radiation Network[39, 41, 42]. For the purpose of this study we will not focus on the comparison between ground station measurements and satellite data. In previous studies the accuracy is widely studied and for the purpose of simulating solar power not within the scope of this study. Its focus lies more on designing a system in which solar power, wind power and a battery work together complying with the predetermined assumptions as stated in section 1.9. Unfortunately real time generation data is not available for the locations chosen and therefore PVGIS [5] is used.

Solar availability is unlike wind availability less fluctuating over the years. In Figure 10 the monthly irradiation (kWh/m^2) is given for the years 2007-2017. Naturally, the yield of a solar farm is more constant over the years.

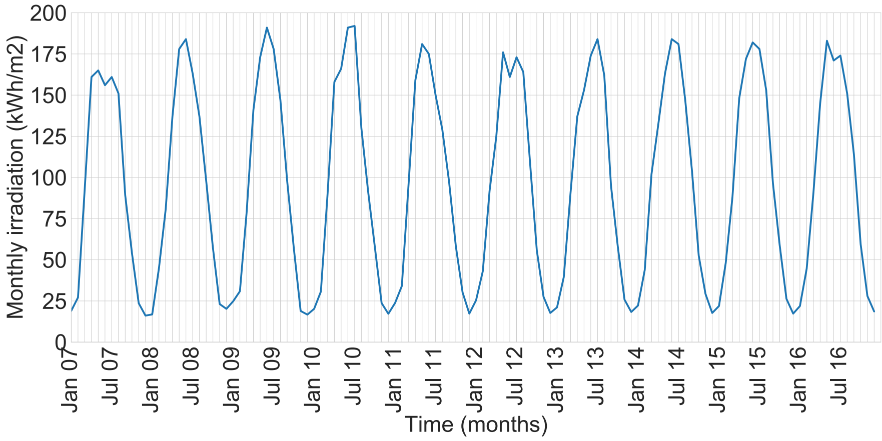
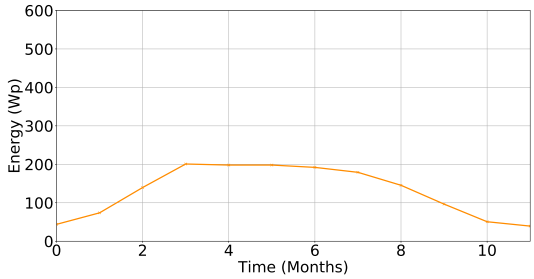


Figure 10: Long-term average solar availability. Source: [5]

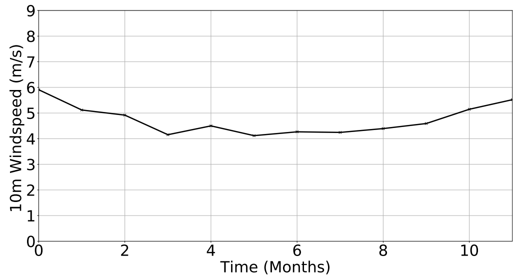
2.2 Simultaneity of Solar & Wind resources

Before the numerical model can be built a better understanding is needed of the fluctuations of both solar and wind resources throughout the years. The sustainable power station incorporates a BESS (short term storage, section 1.4 Battery Energy Storage System) and is thus able to mitigate the diurnal fluctuations. The daily and weekly variability of both wind and solar are shown in section 2.3 and 2.6 respectively. In order to quantify this complementarity 10 year of data is analyzed and shown in Figure 12 for the daily pattern. Similarly in Figure 11 the monthly variation is shown. Data is obtained from PVGIS [5] for the years 2007-2016.

Please note that the solar resources are already converted to power as described in section 2.4 (PV Power).



(a) Seasonality effect of Solar power: 24-hour average

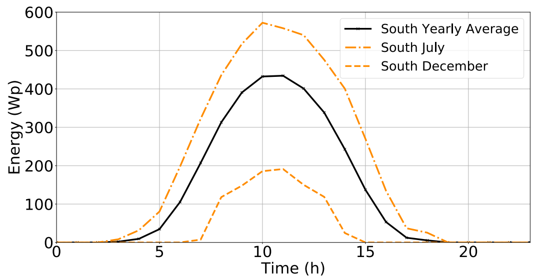


(b) Seasonality effect of Wind power: 24-hour average

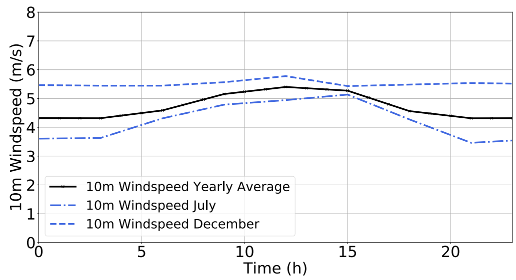
Figure 11: Annual cycle of monthly mean wind speed and solar power output. Note that in this plot the complementarity is shown over the period 2007-2016. Source: PVGIS

It is evident that solar insulation is higher in summer than winter, also the average wind speed is higher in winter than in summer. Seasonally, the combination of wind and solar is strengthening each other and adds value in a higher average output over the year. Wind or solar at its own is using the electrical infrastructure less intensive. In times where new grid connections are sparse, this better usage of the existing infrastructure will help the TSO's in maintaining a safe and reliable grid by introducing more variable generation plants.

As an illustration of the seasonality, Figure 11a reflects the average solar power output for a south oriented 1 kWp installation. Figure 11b provides insight in the average 10m windspeed.



(a) Diurnal effect of Solar power: yearly average



(b) Diurnal effect of Wind speeds: yearly average

Figure 12: Seasonality effect of average Solar and Wind resources for the period 2007-2016. Source: PVGIS[5]

Apart from the seasonal variations in Wind and Solar resources there is also a distinct daily pattern visible in both Wind and Solar resources. In Figure 12a the hourly average solar output is shown. The solar availability is a factor 3 higher at 10am in summer (July) than in winter (December). Concluding from the figure that between 7 pm and 4 am the solar output is zero and will never result in a power output above the cable capacity towards the grid.

The wind speeds in Figure 12b show that the peak availability is also around noon. The benefit of wind energy is that it is also available when the sun is not shining. Modelling of the wind power output and solar power output is needed to analyze the peak power production over time. The distinct variability of both wind and solar on a daily to weekly scale is shown in section 2.3 and 2.6 for a summer and winter week. Analysis of daily to weekly generation profiles have shown that the unavailability in solar resources was complemented by the availability of wind. Also, the unavailability of wind resources was complemented by the availability of solar power. Understanding of how frequently, how long, and when these periods of peak production occur gives an indication for battery sizing.

Numerous papers have explored the variability of integrating both wind and solar power. An extensive review has shown that the complementarity on a daily and seasonal scale was higher than on annual basis[43, 44]. The co-located solar and wind power generation system represents hereby a highly reliable source of power in comparison to standalone systems [43].

Simulation Input

Before modelling of wind, solar power, and to show the simultaneity of solar and wind power production at a typical onshore location in the Netherlands, Westermeerwind windfarm is chosen. Westermeerwind is an (sub)shore windfarm located in the Netherlands in the flevopolder near Emmeloord. The park consists of 48 3MW Siemens wind turbines. Hubheight is 95m and rotor diameter is 108m. The export cable capacity is given for the location and is now set by Tennet at 160 Mega-Volt-Ampere (MVA). At the same location solar insolation data is used to simulate the solar power output as described in section 2.6. The size of the solar farm simulated is for the moment set at 50MWp. This size is large enough to show what happens when the grid capacity is too small at times when both solar and wind production is high and therefore a sensible size before the optimal sizing can be determined. In Table 3 an overview of the used input parameters is given for completeness.

Input Parameters	Value/characteristics
Wind Farm Size	144MW
Hub Height	95 meter
Solar Farm Size	50MWp installed
Photovoltaic System Efficiency	0.9 (10 percent electrical losses)
Farm Efficiency	0.86 (13,7 percent losses, obtained from real generation data)
Shear Coefficient	0.09
Cable/Export Capacity	160 MVA

Table 3: Overview of the used input parameters for the proposed methodology

2.3 Wind Power

In this section the wind power part of the sustainable power station is explained. The step from average hourly wind speed to annual energy production of the wind farm will be explained. In addition, the used wind measurements are then compared with real production data from Westermeerwind windfarm (See Appendix B). This is done to validate the wind climate at the chosen location and look at the degree of uncertainty of the used data sets.

Wind Speed, Efficiency & Power

The average hourly wind speed data, based on a year of data is the input for the annual wind energy production. The wind power is calculated by using the 10m wind speed measured by satellites. The 10m wind is thereafter extrapolated to hub height using the wind profile power law, defined as

$$U_2 = U_1(\frac{Z_2}{Z_1})^\beta \tag{2}$$

where U_2 (m/s) the wind speed at hub height, U_1 the 10 m wind speed is, Z_2 the hub height, and Z_1 the measurement height. Beta (β) is the location specific wind shear exponent, here approximately 0.09. The used wind shear is taken from wind pro for a typical location onshore. The power law is often used in wind power assessments where wind speeds at the height of the turbine >50m must be estimated from observations from near surface ($\sim 10m$). [45] The vertical extrapolation applied tends to underestimate hub wind speeds slightly, which is also thoroughly stated in [46]. For a typical onshore windfarm the Annual Energy Production (AEP) is calculated and slightly scaled by using real production data. Given that real generation data for both wind, and solar is not available for long periods (>8 years) the simple conversion method stated in eq.2 is employed.
For a wind turbine, if the wind speeds exceeds cut-in value, the wind turbine starts to generate. If the wind speeds exceeds the rated speed it starts generating at its rated power; and when the wind speed is higher than the cut-out speed, the wind turbine stops running in order to avoid damage on the generator. The turbine specific power-curve provided by the turbine manufacturer is interpolated to determine the exact power produced at any wind speed.

The wind turbine power output can be taken from the power curve, which is developed at wind speeds under Standard conditions of temperature and pressure (STP). The power curve shows a low cut-in wind speed of 3 (m/s) and a cut-out speed of 25 (m/s).

$$P_{wind} = (PowerCurve((Windspeed)) * N_{turbines} * \eta_{farm} \tag{3}$$

Where P_{wind} is the power generated by the farm, $N_{turbines}$ is the number of turbines and η_{farm} is the farm efficiency. In the current model, an average efficiency of 0.86 (13% losses) is used based on the real output data of the test location Westermeerwind.
Please note that; The calculated power curve data are valid for standard air density conditions of 15 °C air temperature, 1013 hPa air pressure and 1.225 kg/m^3 air density, clean rotor blades, substantially horizontal, undisturbed air flow, normal turbulence intensity and normal wind shear.

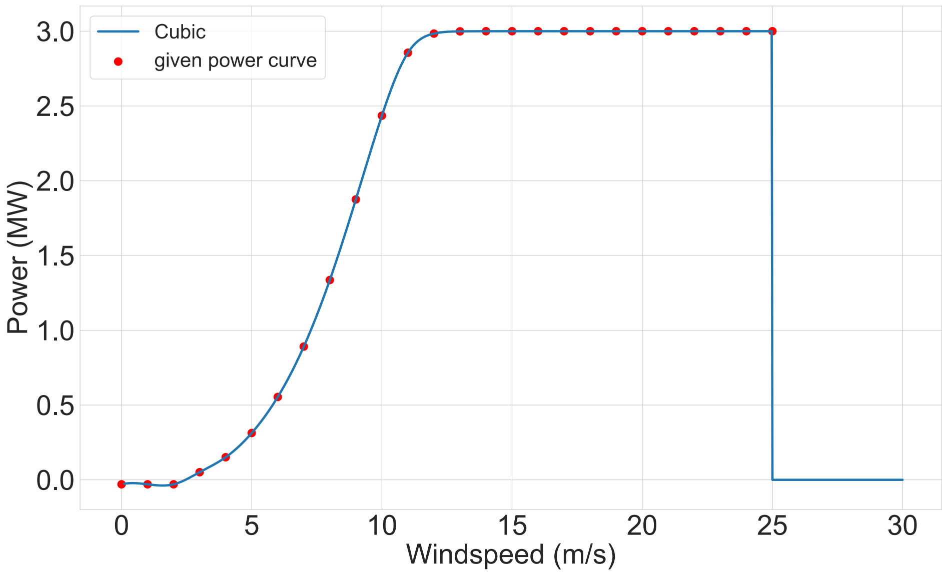
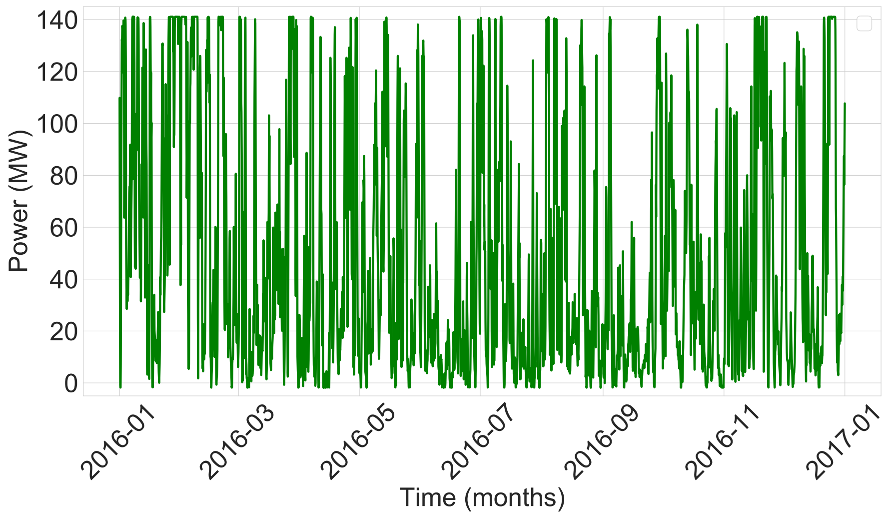


Figure 13: Power Curve Interpolation Siemens SWT-3.0-108 DD

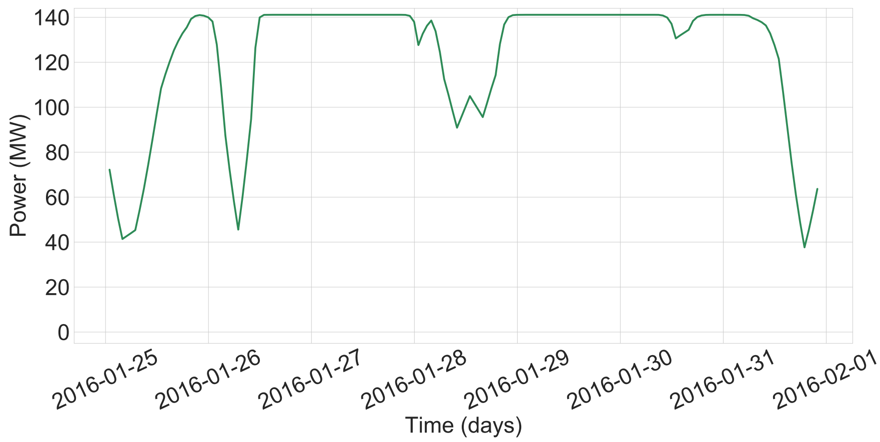
Self consumption of the wind farm is dependent on the turbine specifications. Peak electricity consumption is when the wind turbine is yawing (in Dutch called "Kruien") in order to rotate the cables to their initial position. According to wind energy experts from Ventolines (Ir. Boy Koppenol & Dr. Ir. Bart Ummels) is the self-consumption significantly lower than 1%. In the power curve provided by the turbine manufacturer the self-consumption is already included for wind speeds above cut-in speed till cut-out speed. In Figure 13 the wind speeds below cut-in shows a negative power output to simulate the self-consumption of the wind turbine for wind speeds below cut-in value.

Production Profile Wind

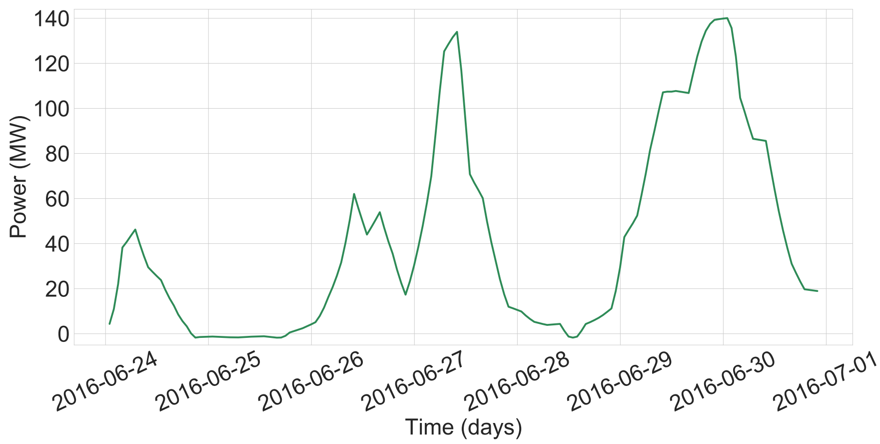
Figure 14 presents the production profile per hour, based on a year of data. The wind AEP for this configuration is 422 GWh. Also, a total of 2935 Full Load Equivalent Operating Hours (FLEOH). Clearly visible is the intermittent behaviour of windspeeds which results in a highly fluctuating power output.



(a) 2016 Full Year



(b) Last week in January 2016



(c) Last week in June 2016

Figure 14: Production Profile Wind (144MWp)

Validation of Simulated Wind Power Output

In Appendix B, the power profile simulated by the model have been compared with the real generation data from Westermeerwind windfarm. The farm consists of 48 3MW Siemens turbines. Hub height is 95 meter. In the figures can be seen that the time of power production varies from the measured generation data. However, the annual energy production is in the same order next to the peak power production is similar. The difference is also due to periods in which the imbalance price was forcing to curtail the turbines in some time-frames. The gain of curtailing is then higher then producing power and delivering the power to the grid. The intended pattern seems from an adequate quality for modelling the simultaneity of both wind and solar.

2.4 Imbalance Wind Farm

This section introduces the concept of imbalance exerted by windfarms. Imbalance is the difference between delivered power P_{wind} and forecasted power $\widehat{P}_{\text{wind}}$. Market experts in the energy sector often refer to this difference in power as imbalance. Market parties must pay the imbalance penalty when there is imbalance energy generated. In section 1.3.3 more info can be found about prices and regulation. The Dutch TSO is at the end responsible for balancing of the grid. Imbalance penalties are invented to reduce the imbalance caused by generating parties. The feed in price (Long imbalance price [EUR MWh^{-1}] (λ^{+})) is for upward regulation and the feed out price (Short imbalance price [EUR MWh^{-1}] (λ^{-})) for downward regulation. Generally, there are two reasons for imbalance, imbalance exerted by wind or by technical issues and thus unavailability. For the year 2018 the imbalance cost due to technical issues was around 20k EURO. The imbalance by wind is much higher. In order to get insight in what the gain would be of producing exact the amount which is forecasted needs to be sorted out via the imbalance prices.

In Figure 15 the imbalance exerted by Westermeerwind is plotted for a period in 2016. Also visible is the forecast which is given 24 hour before generation (powerforecast1day) and the real generation data.

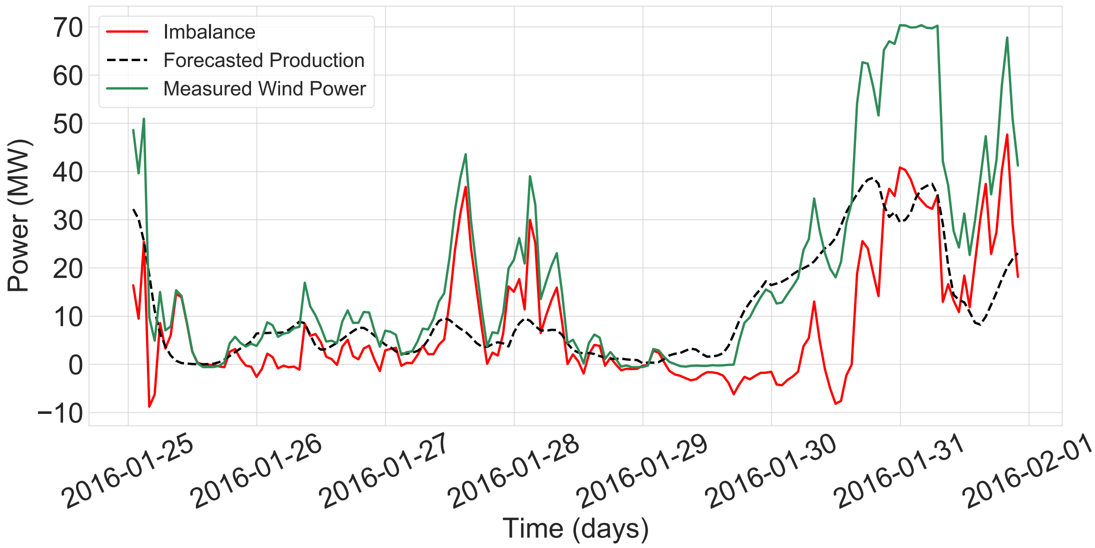


Figure 15: Imbalance, forecasted power production and measured wind power over a week in January, as monitored by Eneco. Data from Ventolines BV.

$$P_{imbalance}(t) = P_{wind}(t) - \widehat{P}_{windforecasted}(t) \tag{4}$$

Where $P_{\text{imbalance}}$ is positive when there is more power generated than forecasted.

2.5 Forecasting Accuracy

This section gives a brief introduction into the concept of wind speed/power forecasting and solar power forecasting followed by a contradictory observance of western countries shifting to a higher share of RES. One of the ultimate goals of power prediction is to estimate the power output early and as accurately as possible. Both wind and solar power become more attractive for system and market parties when model accuracy improves.

The short term wind and solar power forecasting helps in the bidding process in the electricity market. Supply of power more/less than expected creates imbalance in the electricity system. Hence the imbalance markets impose a penalty for this difference between real generation and forecasted generation. Conventional plants do not induce imbalance as they are capable of producing the pre-agreed amount. With the rapid growth of RES and increasing penetration levels, it will be very hard to operate the power grid securely and reliable due to the intrinsic uncertainty and variability of wind power. Bidding the right amount of power is becoming more important when switching to a higher RES penetrated system. For wind and solar power producers this issue is very relevant and needs to be minimized if feasible.

Most of the time, forecasts are done by Numerical weather prediction (NWP) for large-scale areas and long-range forecasting. NWP lacks the ability to accurately predict the stochastic behavior at small temporal and spatial scales [47]. Currently there is a shift going to more detailed forecasting (fine-casting) with meteorological data as input instead of historical data [48].

Increase In Forecasting Accuracy
In Germany the RES capacity has grown from 27 GW in 2008 (7% of the consumed energy) to 78 GW (15% of the consumed energy) in 2015. One would expect that with the introduction of more variable output results in an increase in reserve capacity. However, the TSO announced that the balancing reserves reduced by 15% over this period. This outcome seems to contradict with what seems to be the opposite with common sense [49]. Important to notice is that additional wind and solar power do not mean that it reduces the balancing reserve requirement in itself. What it does indicate however is that there are other factors that are responsible for the outcome. Most likely the improvement of wind and solar forecasts, improvement of understanding of the load pattern, reduced plant outages, and the TSOs might decreased their security margins what resulted in lower costs. Another important notice is that reserves did not increase in Spain, Denmark, and Portugal either with the introduction of more variable RES. It is predicted that at RES shares above 20-30% the reserve capacity will increase significantly. The preceding results described here, are presumably indicating that there is some sort of delay in the need for reserve capacity.

2.5.1 Quantifying Forecast Error

Wind and solar forecast accuracy is typically measured by introduction of the definition Mean absolute error (MAE) [50]. There are several different measures that can be used, but commonly used is the MAE, this helps to conceptualize the magnitude of the error. This is measured with respect to the nominal power of the plant. As the focus in this study lies on the 24-hour window, forecasts obtained are only evaluated on their accuracy in this time frame. The MAE is specified as follows;

$$MAE = \frac{1}{T} \sum_{t=1}^{T} |P_{wind}(t) - \hat{P}_{wind}(t)| \tag{5}$$

Where for each forecast horizon t, the MAE is determined as the average of the absolute forecast errors over an evaluation set of length T. Wind forecasts typically have errors in the range of 10% to 20% MAE of the nominal capacity for a single wind plant. Grouping of wind farms reduces the prediction error [51].
In the same study, forecast errors for offshore wind farms seems to have similar performance

results compared to flat terrain on-shore wind farms.

The MAE is calculated over year 2016 for the used real generation data and forecast time series. Analysis have shown that the MAE is 14.79 MWh, this means a MAE with respect to the nominal capacity of 10% over 2016.

2.6 PV Power

In this section the PV power part of the sustainable power station is explained. From average hourly irradiance values to annual energy production of the PV farm.

Solar Irradiance, Efficiency & Power

The solar radiation received at the ground level, G, known as the global irradiance value (W/m^2) consists of three components. The first one, direct radiation which is the fraction of solar radiation that reaches the ground without being attenuated by the atmosphere and comes directly from the solar body. The second one, known as the diffuse part is the solar radiation that reaches the ground after being scattered by the atmosphere. The third component, is the reflected irradiation from nearby surface or obstacles. In equation 6, the Global Horizontal Irradiance (GHI) is used and can be calculated by summing the Direct, Diffuse, and reflected components.
The efficiency of the PV modules depends on the temperature and solar irradiance. In general the efficiency is nearly constant for irradiance values from about $400W/m^2$ to at least $1000W/m^2$ at a constant module temperature. The module type used in this report is Crystalline silicon solar cells (c-Si) since it is currently the most used panel for large scale applications. PVGIS calculates the effects on irradiance and module temperature using a model described in (Huld et al. 2011).[52]

The power is calculated depending on irradiance(G) and module temperature(T'_m), where G'= G/1000 and $T'_m = T_m - 25$.

$$P_{solar} = \frac{G}{1000} * A * eff_{nom} * eff_{rel}(G, T_M) \tag{6}$$

$$eff_{rell}(G', T'_m) = 1 + k_1 ln(G') + k_2 ln(G')^2 + k_3 T'_m + k_4 T'_m ln(G') + k_5 T'_m ln(G')^2 + k_6 {T'_m}^2 \tag{7}$$

Where eff_{nom} is the panel specific efficiency according to the manufacturer. Similarly, the efficiency deviates from the efficiency at Standard test conditions (STC) with higher temperatures and a variating solar insolation. This is referred to as Relative efficiency (compared to efficiency at STC) (eff_{rel}). The coefficients k_1 to k_6 are found for each PV technology by fitting to measured data at European Solar Test Installation (ESTI) in Italy.[5] In Table 4, the measured coefficients are shown.

Coefficient	c-Si
k_1	-0.017237
k_2	-0.040465
k_3	-0.004702
k_4	0.000149
k_5	0.000170
k_6	0.000005

Table 4: Coefficients (k_i) for the PV power model used for the calculations in PVGIS (Equation 6-7)

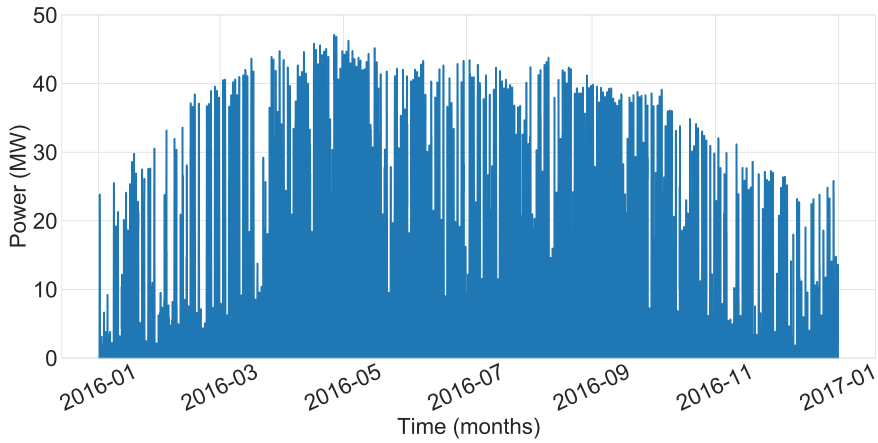
When the sun is shining on the modules the temperature will rise above local air temperature and if there is wind it may help cool the modules. These above-mentionded effects are treated in PVGIS by Faiman et al.[53]

$$T_m = T_a + \frac{G}{U_a + U_b W} \tag{8}$$

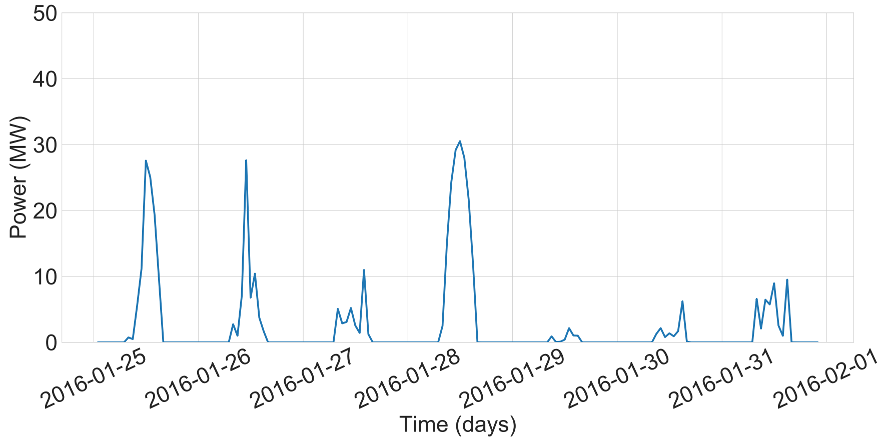
Here, T_a is the ambient air temperature and W is the measured windspeed. The coefficients U_a and U_b have been taken from Table 3 in the paper by Koehl et al. [54] and can be found in Table 3, shown as U_0 and U_1 respectively.

Production Profile Photovoltaic Solar

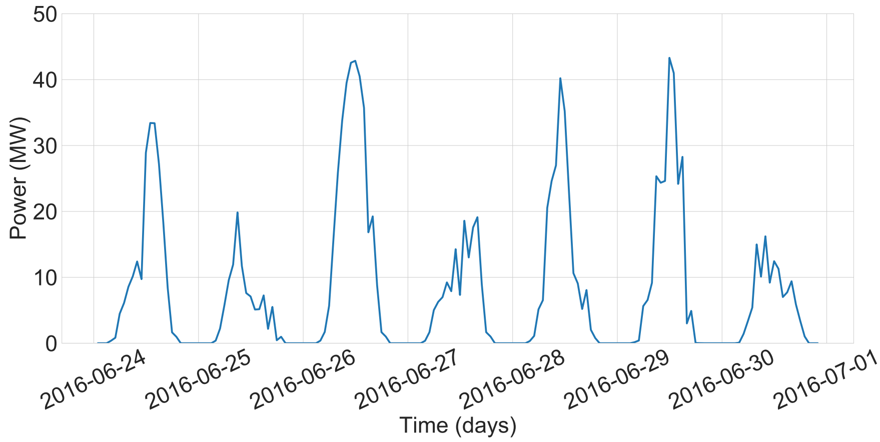
Figure 16 presents the production profile per hour, based on a year of data. The solar AEP for this configuration is 54 GWh. Also, a total of 1059 FLEOH.



(a) 2016 Full Year



(b) Last week in January 2016



(c) Last week in June 2016

Figure 16: Production Profile Solar (50MWp)

Losses of the PV farm

The total electrical system losses are set at 10% to be conservatively (Table 3) Inverter (DC/AC conversion) losses are around 2.0%. Transformer and AC cable losses are completely dependent on the type of cable and the usage of the cables (±2.2%). Reduced availability and other DC losses are estimated on ±3% [55]. The estimated losses due to temperature using local ambient temperature are 8.5%. Cable resistance varies by square when the cable needs to export more power. In this configuration the cable will be used more often and an increasing share at its maximum capacity according to experts from Ventolines (Ir. Boy Koppenol & Dr. Ir. Bart Ummels).

In the calculation provided in section 2.6, the temperature dependency (thermal losses) is already present. Evidently, solar panels work most efficiently when they face directly the sun. In order to achieve the best annual energy production the optimum angle and azimuth is calculated by PVGIS[5]. In Figure 17, is shown how one defines the orientation of a solar panel. The optimum angle (vertical tilt of the solar panels) is 39 degrees south orientated and zero azimuth (horizontal orientation of the panels with respect to the equator) for the location of Westermeerwind. In addition the power of pv modules tends to decrease slowly with age. Jordan et al [56] found that PV modules typically lose about .5% power each year at maximum. With an expected lifetime of around 20 years this would mean that the power produced after 20 years is 90% of the initial power. It is assumed that the total installed capacity remains the same by adding new panels. since optimization on a daily to weekly time scale is sought this is not explicitely modelled. Standard crystalline silicon solar panel are assumed without solar tracking. Self-consumption of the solar PV park is negligible and therefore not considered in this study.

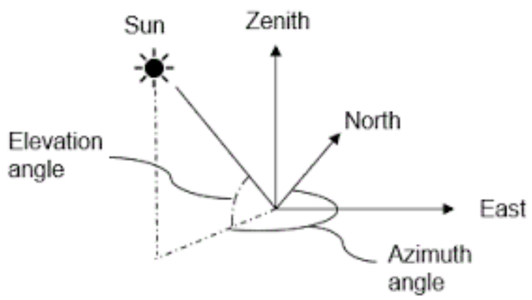


Figure 17: Solar Elevation Angles for panel orientation

2.7 Electrical Energy Storage System

In this section the specifications of the Lithium-ion battery will be explained and the concepts of lifetime, c-rate, Depth of discharge (DOD), State of Charge (SOC), self discharge, and costs are discussed. Additionally the assumptions and input parameters for the battery model are given.

2.7.1 Lithium-ion Battery

The desired battery voltage and current can be obtained by connecting the battery cells in series (Voltage) and in parallel (Current). The capacity of a battery refers to the amount of energy that can be stored in the system. For utility or EV systems, or stationary storage systems, a capacity is described in kilowatt-hours. For example, a 100-kWh battery can provide 100kW continuously for one hour. The SOC of a battery refers to the amount of available energy remaining in the cell compared to its rated capacity. It is therefore a value ranging from zero when fully discharged to one when fully charged. DOD of a battery refers to the energy extracted by a battery bank during a discharge cycle, compared to the total rated capacity of the battery.

$$SOC = 1 - DOD \tag{9}$$

The power (kilowatts, kW) refers to instantaneous output. The amount of electricity generated or discharged at a given moment. In large BESS power is usually measured in Megawatts (MW 10^6). Energy (kilowatt-hours, kWh) often denoted as battery capacity, on the other hand is a measure of the amount of energy over time. Usually it is given in Megawatt-hours (MWh). To conclude, a Watt-hour is the voltage (V) that the battery provides multiplied by how much current (Ampere) the battery can provide for a moment of time (in hours). Therefore, Voltage * Amps * hours = Wh.

The rate of charging and discharging is referred to as the C-rate of a battery, where C stands for the capacity (Energy) of a battery available for discharge. The capacity of a battery in ampere-hours is usually rated at 1C optimally. This means that in one hour the battery can be discharged from full to zero, and vice versa in one hour can be charged to full. Further, a 4Ah battery can provide 4 amperes continuously for one hour. If the battery is discharging at 0.5C (or C/2), the battery will provide 2 amperes for two hours straight. The relation between C-rate, power and energy capacity of a battery is described in equation 10.

$$C_{rate} = \frac{Power}{Energy}\ (per\ unit\ time) \tag{10}$$

When a battery is charged and discharged the lifetime of the battery will reduce. With every cycle the usable range of the battery capacity will slowly decrease. Cycle ageing is affected by temperature, Depth of discharge and operating current. [57] Still the exact behaviour of large battery systems is poorly understood. During a battery's lifetime, its performance lowers gradually due to physicochemical transformations degrading energy (capacity) and power (impedance) capabilities of the battery [57]. A review of existing literature and chats with market experts from Super-B, Alfen Batteries, and Hartel 2 (June 2019) confirmed that a large scale battery system can handle 5000-6500 cycles before only 60% of the initial capacity is still usable. Degradation over time is estimated at around 2% per year. In general, with low operating temperatures, a limited DOD, and low so-called c-ratings (not above 1C) this should be possible. Deviating from the before mentioned will increase cycle aging and deteriorates the battery lifetime and business case.

As mentioned earlier, the requirements needed for a sustainable power station matches the best with a lithium-ion battery. Lithium-ion batteries have favourable characteristics for fast and powerful discharging, however there are limiting factors in the usage of the system. These crucial limitations are captured in parameters used as input in the control of the sustainable power station, as well as for modelling and optimization purposes. The parameters that influence the capability of the BESS are shown in Table 5 and used as input for the model proposed in section 4.

Characteristics

Input Parameter	Value/characteristics
Cell type	lithium iron phosphate (LiFePO4)
Cell specifics	3.2V and 90Ah
C-rate	C/1 at room temperature
Battery capacity	..MW
Battery energy	..MWh
Roundtrip efficiency	80% (10% - 90%)
Lifetime	3000-5000 cycles
Charge efficiency (η_{charge})	0.95
Discharge efficiency ($\eta_{discharge}$)	0.95
Battery Capex ($C_{Battery}$)	450K MW^{-1}

Table 5: Battery characteristics used as input parameters

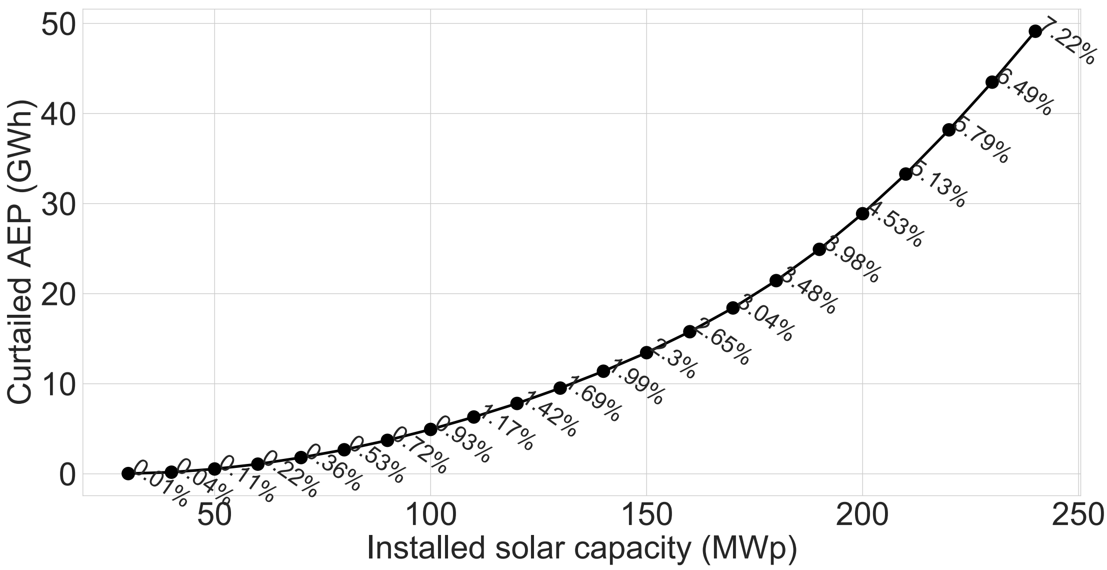
3 Simultaneity Solar & Wind Power Output

This chapter focusses on the simultaneity of Wind power and Solar PV power plant where the electrical infrastructure introduces a production limit. The aim is to quantify necessary curtailment volumes under various configurations of the solar farm.

3.1 Curtailment Analysis

In the Netherlands, solar PV production above half of its installed capacity takes place less than 10% of the time. In a combined plant the occurrence of peaks of both wind and solar are even lower. Curtailment occurs when the combined production level of wind and solar PV exceeds the export capacity. For optimal usage of the existing infrastructure it is important to quantify power production from wind and solar irradiation, but also the limiting mechanisms of the electrical infrastructure. In general the maximum cable capacity is reached when a certain temperature is reached, this is often translated to a maximum power that can be transported for a long or indefinite period of time.

Please note that here, and in the prior sections 2016 is used since this is a year where PVGIS [5] database matches with real generation data of the Westermeerwind farm for verification purposes. Overplanting wind and solar capacity on a vast grid connection of 160MVA leads to power curtailment when resources are abundant. The full potential is not utilized and therefore reflected by Annual Curtailed Energy for multiple solar PV farm sizes.



2

Figure 18: Curtailment Summary. 160MVA export limit. (% Total AEP plotted on bullets)

As can be seen during periods of high wind and solar availability (See Figure 19) the cable capacity is limiting and the wind farm or solar farm needs to be curtailed at this cable capacity. The outcome of the curtailment analysis shows an interesting result, significant overplanting can be achieved whilst maintaining a limited level of curtailment. To exemplify, let us take a 144MWp Wind farm and a 225 MWp Solar farm that boosts the installed capacity to 369MWp. The electrical infrastructure is laid out to transport 160MVA. The total volume of energy to be curtailed in such year is 51 GWh or 7.22% (of total AEP, 700 GWh). This is also only happening in Summer months.

Moreover, as can be seen in Figure 18 with 50MWp Solar PV installed the energy which cannot be transported due to the limiting electrical infrastructure is here only 0.11% (of total AEP, 484 GWh). This means that more than 99% can be transported without the need for storage. In total this happens 106 hours in a year, analysis showed that this comes to 46 days in a year. Please note that sizing of the solar farm here is not optimal but seems appropriate for now to show the simultaneity (both Solar and Wind) of peak power production at the site.

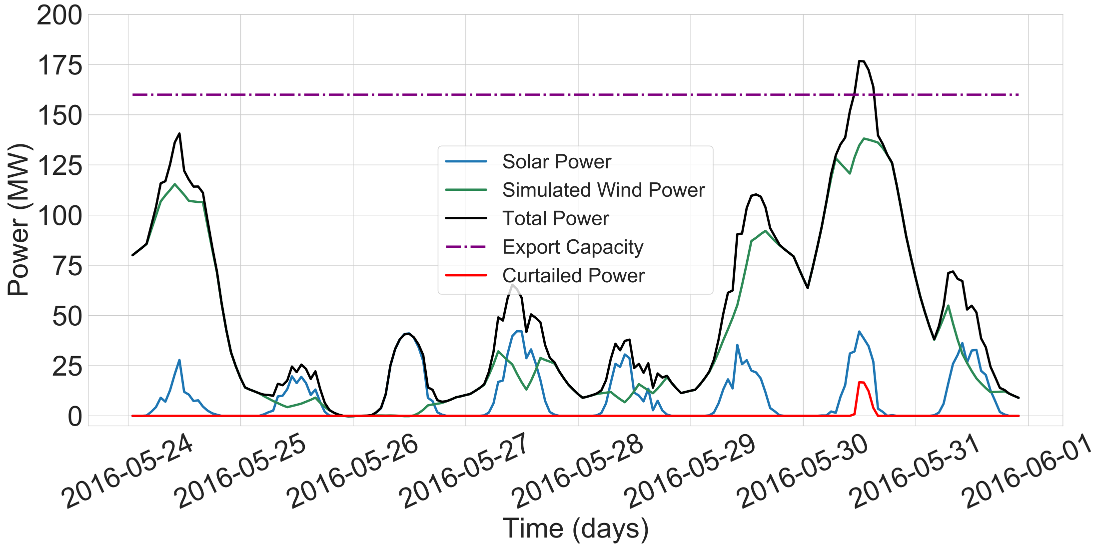


Figure 19: Curtailment Analysis, 50MWp Solar, and 160MVA export limit

In Figure 19, simultaneity is shown for a week in May 2016. This figure shows what can happen when simultaneity of both wind and solar resources are high at the same moment in time. At the 30$^{\text{th}}$ of May the total power produced is higher than the export capacity at 9am, every following hour the infrastructure is still limiting and this energy needs to be stored or curtailed as well. The energy in these hours needs to be summed up to indicate how large these energy volumes are. In order to get an indication how often this is, and how long these periods last an analysis has been performed to examine these periods with high wind and solar availability.

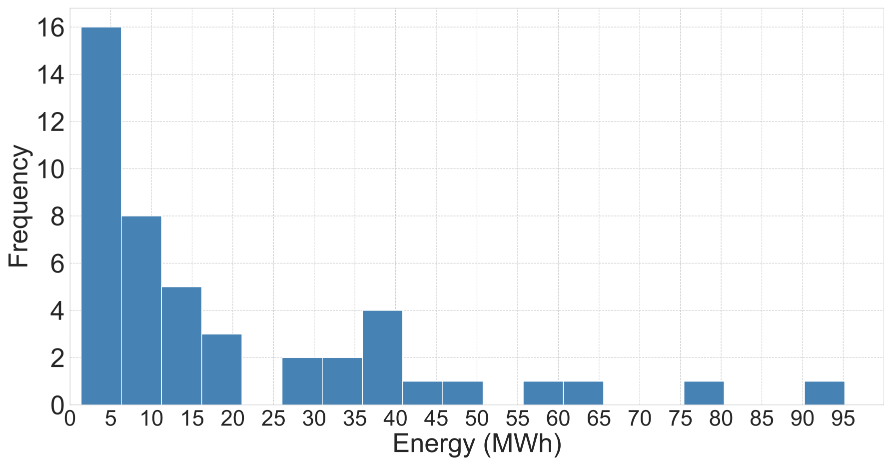


Figure 20: Probability Density Function, 50MWp Solar, and 160MVA export limit

In Figure 20 the periods for the year 2016 are displayed in a probability density function. The average curtailment size is 20 MWh. The minimum excess energy is 1 MWh and maximum excess energy during a day is 95 MWh.

4 Modelling Approach

To be able to calculate the optimal configuration, the different models needs to be expressed as optimization problems. In this chapter, first the Battery Model is described with all the underlying mathematical principles and optimization rules. Subsequently, the modifications for the Imbalance Model and Battery PV Model with respect to the Battery Model are described. Mathematical optimization is a process of looking for the optimal outcome of the objective function subject to constraints and variables. The underlying mathematical principles are set following the assumptions presented in subsection 4.1.1. In section 4.2 the different objective functions are presented. Section 4.3 presents the constraints which are set to solve the optimization problem.

The tools used for implementing these models are the Pyomo [58], Numpy, Scipy, Pandas libraries in Python 3. The optimization models are solved using the GLPK solver for linear mixed integer programming and IPOPT for non-linear mixed integer problems compatible with Pyomo. Both solvers are open source and publicly available.

4.1 Problem formulation of the optimum design

The model reflects a realistic optimization scenario for the stated problem. Using one type of storage instead of different technologies provides a manageable model. Since the BESS is considered to be a li-ion battery, the battery is able to directly charge or discharge at a high rate. In this study, the main objective is to find the most cost optimal design for a sustainable power station in which the existing grid connection is used more intensively. The model maximizes the profit and determines the optimal sizing for the solar PV farm and BESS. By changing the objective function the optimization algorithm is able to determine the optimal BESS size (size of the battery system [MWh] ($K_{battery}$)), apply arbitrage, minimize the imbalance exerted by the sustainable power system, and calculate the trade-off between curtailment and BESS sizing.

4.1.1 Assumptions

The conceptual model of the sustainable power station is formulated to define the individual models step-by-step. The combination of the three models will give insight in the optimal configuration of the sustainable power station. Before the mathematical relations can be demonstrated the assumptions are listed below.

First, it is assumed that the battery is responsible for maintaining that all excess energy will be stored in the battery at all times. Hereby using all the renewable energy generated by the wind and solar farm. Secondly, the BESS is solely charged by wind and solar energy. Energy can not be taken from the grid. Thirdly, the sustainable power station is designed on the electrical infrastructure from the existing wind farm. Hereby assuming that the net connection can be shared whereas cable pooling (sharing a grid connection by wind and solar) makes it possible to use the pre-existing connection cable without the need for extra investment. In section 6.1.2 the additional gain of sharing this connection will be discussed extensively. Fourthly, the cost of installation of the BESS is expressed in Capital expenditures (EURO) (CAPEX). The optimization algorithm takes a linear part of the CAPEX whereas the salvage value is zero at the end of the lifetime. The amortization of the BESS is also assumed to be linear. Fifth, it is investigated if the sustainable power station is able to be a (significantly more) balance responsible party on its own. The mismatch between production and forecasting could be partially settled within the sustainable power station. The final assumption is that the size in which the sustainable power station will operate at the markets is small and thus will acts as a price-taker instead of a price maker.

4.1.2 Grid-connected Hybrid System Overview

Figure 21 illustrates how the solar PV farm, wind farm, and BESS are connected and how they are connected to the grid. Generally, a wind farm is generating Alternating current (AC) and this needs to be converted into Direct current (DC) first before it can be stored in the BESS. When the power generated by the wind farm needs to be transported directly to the grid, this power is typically converted from AC to DC and then again to AC (inverted). The solar PV farm generates DC and can thus be stored directly in the BESS. Most frequently, there is no limiting electrical infrastructure. In such cases this solar power needs to be inverted first before it can be fed on to the grid.

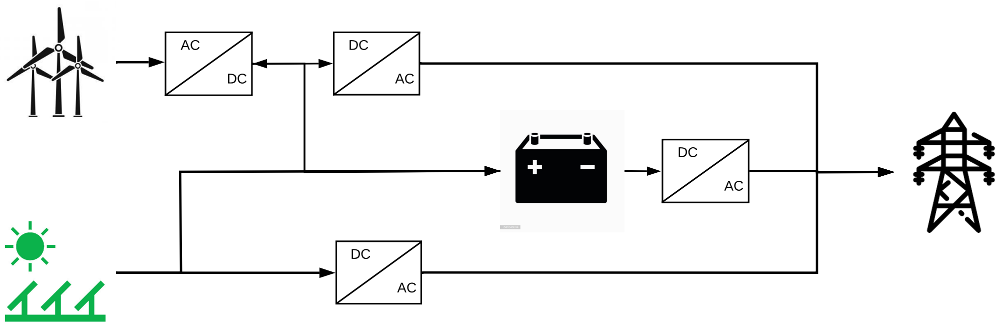


Figure 21: Schematic diagram of grid-connected HRES

4.1.3 Variables, Sets, and Parameters

The APX price, Solar power, Wind power and Wind forecast for every hour is formulated as an input parameter indexed over time. The system variables $\mathrm{P_{togrid}}$, $\mathrm{P_{in}}$, $\mathrm{P_{out}}$, $\mathrm{E_B}$, and $\mathrm{P_{curt}}$ are bounded for every t as stated in Table 6. The bounded variable $\mathrm{K_{battery}}$ is not varying with t but is constant for the optimized time slot. $\mathrm{P_{Batt}}$ is the battery power, later referred to as $\mathrm{P_{in}}$ (Charging Power) and $\mathrm{P_{out}}$ (Discharging Power).

Additionally, restrictions are included;

- SUM of $\mathrm{P_{solar}}$, $\mathrm{P_{wind}}$, and $\mathrm{P_{batt}}$ is limited by the Cable capacity ($\mathrm{P_{togrid}}$), $\mathrm{P_{togrid}}$ is Non Negative for every t since taking electricity is not allowed (See Eq 21).

Fixed Input Parameters	Value/characteristics
Wind power at index t - P_{wind}	(MW)
Forecasted wind power at index t - $\widehat{P}_{\text{wind}}$	(MW)
Solar power at index t - P_{solar}	(MW)
APX price at index t - APX_{price}	(Euro $\mathrm{MWh^{-1}}$)
Parameters	**Value/characteristics**
$\mathrm{E_B}$ at t=0	0.0 MWh
η_{charge}	95%
$\eta_{discharge}$	95%
τ, Time step	1 hour
α, Imbalance price	± 4.0 Euro $\mathrm{MWh^{-1}}$ see Appendix E
ρ_1	50
Output Variables	**Value/characteristics**
Total exported power - $\mathrm{P_{togrid}(t)}$	0.0 - Cable Capacity (MW)
Charging Power - $\mathrm{P_{in}(t)}$	0.0 - ∞ (MW)
Discharging Power - $\mathrm{P_{out}(t)}$	0.0 - ∞ (MW)
Battery level - $\mathrm{E_B(t)}$	0.0 - ∞ (MWh)
Optimal ESS size - $\mathrm{K_{Battery}}$	0.0 - ∞ (MWh)
Optimal solar PV farm size - $\mathrm{K_{Solar}}$	0.0 - ∞ (MWp)

Table 6: Overview of the used input parameters and variables for the optimizer

Note: The penalty factor ρ, will be introduced in Equation 15.

4.2 Objective Function(s)

In this research, the fundamental goal of the proposed model is to calculate the most cost optimal design for a sustainable power station. The design is found by using different objective functions for the different sub models. The generic objective (Eq. 11 is to maximize profit. Satisfying the aforementioned requirements of no self-consumption from the grid, zero curtailment and minimizing the imbalance caused by the wind farm. The total power to the grid is therefore multiplied by the APX price minus the CAPEX of the BESS and Solar farm. The CAPEX are scaled with the simulation length linearly with respect to the lifetime (See equation 13).

4.2.1 Battery Model, Linear Optimization Initialization

In the Battery model, the optimal storage size $K_{battery}$ [MWh] will be determined using hindcasting. The BESS cannot be too small because sizing is done by meeting all constraints during the optimized period. As mentioned before, the objective of this model is to maximize profit for a sustainable power station. Satisfying the aforementioned requirements of no self-consumption from the grid never curtailing energy due to a limiting electrical infrastructure. The total power to the grid is therefore multiplied by the APX price minus the cost per MW installed for both the

BESS and the solar farm (see Eq 13b). This function will be used and explained simultaneously with the results presented in Chapter 4 (Model Verification & Validation).

$$\textbf{Obj. Function} : Maximize\ Profit = Revenues - Capex \tag{11}$$

$$Revenues : \sum_{t=1}^{T} P_{togrid}(t) * APX_{price}(t), \quad \forall t \in \{1, 2, \dots T\} \tag{12}$$

[with T=1..n], where n is length dataset.

In this design phase of the model, the objective is to find the optimal size of the BESS. It is assumed that the generation data of both the wind farm and solar farm is given as well as the size of the solar PV farm. The size of the BESS in the sustainable powerstation is determined by finding the optimal battery capacity.

Equation 13 provides the cost per MW installed for both the BESS and the PV farm. Where K_{solar} is the solar PV farm size in MW and $K_{battery}$ the BESS size in MWh. These two variables are both independent of time. All the other variables used in the model are time dependent. Similarly, the battery and solar PV farm Capex is denoted as C_{solar} and $C_{battery}$ respectively. The Capex is annualized (linearly) via Eq.13a and Eq. 13b to ensure the model is using a portion of the cost proportional to the length of the optimized dataset.

$$C_{battery} = \frac{C_B * \Delta t}{lifetime\ battery} \tag{13a}$$

$$C_{solar} = \frac{C_{PV} * \Delta t}{lifetime\ solar} \tag{13b}$$

Where Δ t is the length of the simulation.

$$Capex = K_{solar} * C_{solar} + K_{battery} * C_{battery} \tag{14}$$

Furthermore an incentive is included in the objective function which penalizes charging and discharging at the same moment in time. The Penalty factor (ρ_1) factor is chosen at 50 to be sufficient. When this penalty is not introduced, the net power of the battery is correct but the P_{in} and P_{out} can both be positive. The battery power (P_{in}-P_{out}) is always correct. However, the model does not distinguish between a P_{in}=40 and P_{out} =10 which results in a battery power of 30MW. Or P_{in}=30 and P_{out}=0. The latter is preferred since the charge and discharge losses are calculated using the individual components (P_{in} and P_{out}) of the battery as explained in Figure 22.

$$-\sum_{t=1}^{T}(\rho_1 * P_{out}(t) - P_{in}(t)), \quad \forall t \in \{1, 2, \dots T\} \tag{15}$$

In conclusion, the complete objective function used is stated in equation 16 and contains the arbitrage term which incentivizes discharging of the BESS, the ρ term which penalizes discharging and charging simultaneously, and the annualized CAPEX of both the solar PV farm and BESS.

obj Function :

$$\sum_{t=1}^{T} P_{togrid}(t) * APX_{price}(t) - \sum_{t=1}^{T}[\rho_1 * P_{out}(t) - P_{in}(t)] - (K_{solar} * C_{solar} + K_{battery} * C_{battery}),$$
$$\forall t \in \{1, 2, \dots T\} \tag{16}$$

Note: $\mathrm{K_{battery}}$ is computed and $\mathrm{K_{solar}}$ is assumed in the Battery model(1) and imbalance model(2). In the third model (Battery PV Model), both $\mathrm{K_{solar}}$ and $\mathrm{K_{battery}}$ are outputs of the model.

4.3 Constraints

The constraints consists of two types:

1. Equality constraints; defining a variable or set of variables equal to a certain value or other (sets of) variable(s).
2. Inequality constraints; defining a variable or set of variables less than a certain value or other (sets of) variable(s).

Inequality constraints
The amount of energy which can be transported to the grid is limited by the maximum cable capacity, $\mathrm{P_{Cablemax}}$ (see Eq. 17).

subject to (s.t.)

$$P_{togrid}(t) \leq P_{cablemax}, \quad \forall t \in \{1, 2, \dots T\} \tag{17}$$

Equation 18 ensures that the battery level for every t, is lower than the optimal battery size quantified ($\mathrm{K_{battery}}$) at all times (within the lower charging limit (E_{B-}) and upper charging limit (E_B^+) of the BESS. Battery level is described as Energy stored in battery [MWh] (E_B)). Typically in battery modelling the lower and upper charging limits are between 10 to 90% depending on the technology considered. In order to maintain the battery lifetime these limits may never be exceeded.

$$E_B(t) \leq 0.9 * K_{battery}, \quad \forall t \in \{1, 2, \dots T\} \tag{18a}$$

$$E_B(t) \geq 0.1 * K_{battery}, \quad \forall t \in \{1, 2, \dots T\} \tag{18b}$$

The definition of the maximum power out and power feed into the BESS is stated in equation 19, relating the c-rate of the battery. In order to minimize battery degradation it is assumed that the battery charge and discharge limit is set at 1C.

$$P_{inmax}(t) \leq \frac{K_{battery}}{\tau}, \quad \forall t \in \{1, 2, \dots T\} \tag{19a}$$

$$P_{outmax}(t) \leq \frac{K_{battery}}{\tau}, \quad \forall t \in \{1, 2, \dots T\} \tag{19b}$$

With τ=1 hour. Finally, the generation output for the solar PV farm and Wind farm at any time-step t, is always smaller than the installed capacity of the used technology.

$$P_i(t) < P_i(Wp), \quad \forall t \in \{1, 2, \ldots T\} \tag{20}$$

Where i, is the type of RES and Wp is the installed capacity of the associated RES.

Equality constraints

The energy balance equation (Eq. 21) is formulated where at all times the P_{togrid} is equal to the sum of P_{batt}, P_{wind}, and P_{solar}. Where P_{wind} is the wind power output at moment t in time and P_{solar} is the solar power output at moment t. Moreover, P_{in} is the power in and P_{out} is the power out of the battery at every t.

$$-P_{togrid}(t) - P_{in}(t) + P_{out}(t) + P_{wind}(t) + P_{solar}(t) = 0, \quad \forall t \in \{1, 2, \ldots T\} \tag{21}$$

Figure 22, provides an overview of how the storage system is modelled. The model is able to transport the energy directly to the grid or store in the battery for later use during periods of limiting electrical infrastructure.

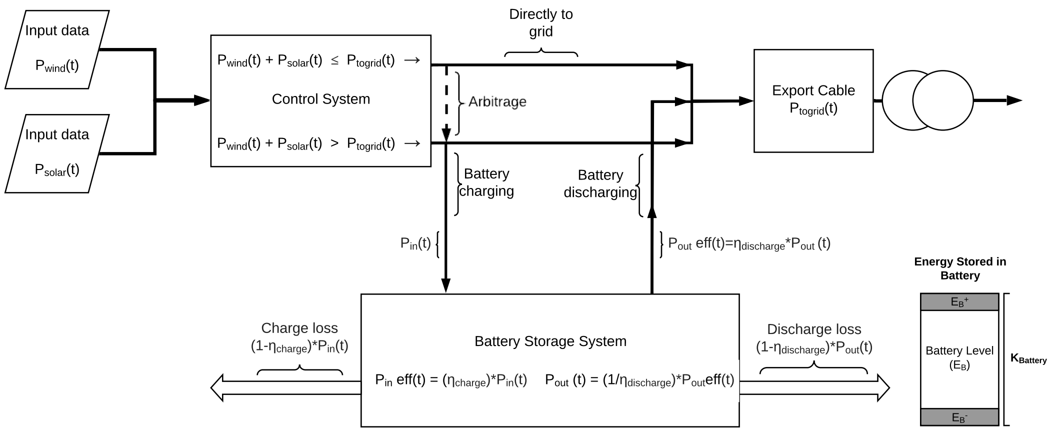


Figure 22: Energy flow Diagram BESS and control system box at t=0. All the generated power is directly transported to the grid. Discharge and charge losses are depicted by blank arrows.

Battery level

The available energy of the battery at any given moment is referred to as the battery level (E_B) in MWh. The battery level changes over time during charging and discharging. Energy going in the battery during charging must be multiplied with the charge efficiency before it can be added to the battery level. This is also valid for discharging. The difference in battery level for two consecutive hours is the difference in charging and discharging at that time. In Appendix C a simplified example is given for the BESS during limiting electrical infrastructure (charging) and during discharging. Moreover, when the BESS is applying arbitrage is visualised

Equation 22 ensures that the stored energy will change for the next time step during charging and discharging. Note that the battery cannot charge and discharge at the same moment in time.

$$t = 0: \quad E_B = E_B(0) \tag{22a}$$

$$t > 0: \quad E_B = E_B(t-1) + \eta_{charge} * P_{in}(t) - \frac{1}{\eta_{discharge}} * P_{out}eff(t), \quad \forall t \in \{1, 2, \ldots T\} \tag{22b}$$

$$P_{batt}(t) = P_{in}(t) - P_{out}(t), \quad \forall t \in \{1, 2, \ldots T\} \tag{23}$$

4.4 Imbalance Model, Non-linear Optimization Initialization

The main purpose of the Imbalance Model is looking for the optimal battery size where imbalance is minimized (e.g. ensuring a more reliable generation profile).
By introducing Equation 24a the model is able to minimize the imbalance caused by the wind farm. This problem is non-linear and requires a solver which is able to solve non-linear problems. In this model the IPOPT solver for Pyomo is used. The optimal solution is found by introducing a so called tracking problem which gives a penalty when imbalance is feed on to the grid. Please note that by introducing this quadratic term positive imbalance is minimized as well as negative imbalance. It is penalized in both directions with the same 'weight'. In reality when the imbalance long-price is positive which it is most of the time, no penalty is given but instead the long-price (λ^+) is received. Only when the long-price is negative imbalance exerted by the wind farm will 'cost' money. Presumably it is economically more feasible to store this energy and sell it when the price is high, using arbitrage.

The battery power minus the imbalance power squared times the penalty factor forces (α) the model to minimize imbalance. By applying a higher penalty the change in profit can be determined. When the gain of minimizing is lower than alpha this imbalance is not eliminated by the battery. In Appendix E the λ^+ and λ^- have been analyzed by using real generation data of a wind farm and the corresponding day-ahead forecast to determine the precise value of imbalance. Typically the cost of every MWh of imbalance lies in the range of 2-10 EUR MWh^{-1} but depends on many factors (such as forecasting accuracy, long and short price imbalance market, solar & wind availability, and level of RES active in a region). The model is formulated allowing that first excess energy is stored (periods that the combined generation of both wind and solar is higher than the cable capacity) and secondly the exerted imbalance is minimized by the BESS.

$$\textbf{Obj. Function} : Max.Profit = Revenues - Capex - \alpha * \sum_{t=1}^{T} (-P_{out}(t) + P_{in}(t) - P_{imbalance}(t))^2 \tag{24a}$$

Where $\mathrm{P_{imbalance}}$ is the imbalance power for every moment in time related to the real generation profile of a specific wind farm.
Note: Substantial imbalance is penalized more due to the quadratic term.

4.5 Battery PV Model, Non-linear Optimization Initialization

The conceptual Battery PV Model determines the optimal size of the solar PV farm [MWp] (K_{solar}). In the previous models an approximated size (based on the Curtailment analysis, section 3.1) is chosen which was sufficient to show that during peak production of both wind and solar PV the electrical infrastructure was limiting. Curtailed energy was not allowed. (e.g. all the energy which can be generated is used). The Battery PV Model however, is looking for the optimal size of adding a solar PV farm and BESS to an existing wind farm.
In this model the optimal size is determined based on the Capex of the solar PV system and the additional gain of installing an extra MWp. The model is able to calculate the profit for every possible size (see equation 14), where every (extra) MWp installed capacity should result in a higher profit. The model is looking for the trade off between using a larger BESS or utilizing a smaller solar PV farm. The proposed model is able to curtail a limited amount of solar power as stated in equation 26 as long as this will result in a more optimal outcome. By granting a limited amount of curtailed solar power a more realistic outcome is obtained whereas sizing both solar PV farm size and BESS without curtailing is not what will happen in reality. By releasing this assumption in this third, and last battery sub model the algorithm is able to look for the most optimal configuration in terms of sizing. Currently the available grid scarcity is already delaying the build-out of new renewable energy plants and thus designing an optimal configurations is chosen to be more important than preventing having curtailed energy at all times.

Constraints & Objective Function
The optimal solar farm size is denoted by K_{solar} and is a time-independent variable. Equation 25 states that the solar power output (denoted by PV_{out}) is between zero and the maximum solar power output of a 1 MWp solar PV farm times the optimal solar farm size (K_{solar}). The simulated solar power output is $P^{n}{}_{solar}$ and is referred to as the normalized solar power (which is between zero and the maximum solar power output of a 1 MWp solar PV farm).

$$0 \leq PV_{out}(t) \leq K_{solar} * P^{n}_{solar}(t), \quad \forall t \in \{1, 2, \dots T\} \tag{25}$$

Where PV_{out} is a time dependent variable bounded from 0.0 to ∞ and $P^{n}{}_{solar}$ is the normalized wind input parameter. The model is looking for the optimal outcome based on the annualized CAPEX of the solar PV farm and BESS. Consequently, it can be more beneficial to size the solar PV farm and BESS allowing a minimum amount of curtailed solar energy. Economically this is more beneficial then over-sizing the system components. Curtailing a limited amount of solar power is therefore granted.

$$P^{solar}_{curt}(t) = K_{solar} * P^{n}_{solar}(t) - PV_{out}(t), \quad \forall t \in \{1, 2, \dots T\} \tag{26}$$

Moreover, the balance equation is slightly adapted by using the optimal solar power output denoted by PV_{out}. Here also the model is not able to take electricity from the grid and is only able to feed electricity towards the grid.

$$-P_{togrid}(t) - P_{in}(t) + P_{out}(t) + P_{wind}(t) + PV_{out}(t) = 0, \quad \forall t \in \{1, 2, \dots T\} \tag{27}$$

5 Model Verification & Sensitivity Analysis

Modelling and simulation play a key role in optimal design of complex energy systems. It is assumed in this thesis that the short-term optimization structure is capable of wind, solar and battery power in an aggregate simulation. Before the proposed model can be used a two step-approach has been conducted. Generally a conceptual model is verificated and validated before the results can be interpreted. Verification is checking if the system is designed in the right way. Is every equation used, formulated and programmed correctly. Validation instead, is done by checking if the model acts in accordance with measurements from a real system or test set-up. As mentioned in section 1.7 the proposed design is different from existing set-ups and can therefore not be validated easily.

The model is verificated by looking at conservation of energy and if it acts as intended. The verification section uses a solar and wind input which can be solved analytically. Furthermore a sensitivity analysis have been carried out by means of increasing the input parameters (Capex solar PV farm , Capex BESS, and alpha factor) linearly.

5.1 Optimal Battery Size

5.1.1 Analytical Verification Battery Model

In this section the BESS model is verificated by using a simple input function for the solar and wind generation data. The solar power production is replaced by a sinefunction and can be found in equation 28. The wind power production is replaced by a step-function which can be found in equation 29.

The intention of the simplified input is to show the correctness of the battery model. Hereby showing that the proposed model satisfies the law of conservation of energy at all times. In Physics and Chemistry this law is often used to show that the total energy of an isolated system remains constant over time. This law states that energy may never be created nor destroyed. The control system in the model (see Figure 22) is programmed following the balance equation 21 in which energy is stored when total generation is above the export cable limit and electricity can be discharged when total power is lower than the export cable limit (i.e. there is unused cable capacity).

$$f_{solar}(t) = A * sin(\omega t) \tag{28}$$

A complete sine function, is a periodic function that goes through one complete cycle when t=2π. The function used here is only for π and thus a half cycle. Only the positive part is used in the verification.

$$f_{wind}(t) = \begin{cases} 0 & t < t_1 \\ W & t_1 \leq x \leq t_2 \\ 0 & t \leq t_3 \end{cases} \tag{29}$$

$$f_{cable}(t) = C \tag{30}$$

Where t is the time in hours. Each hour is $\frac{1}{24}\pi$ period long.

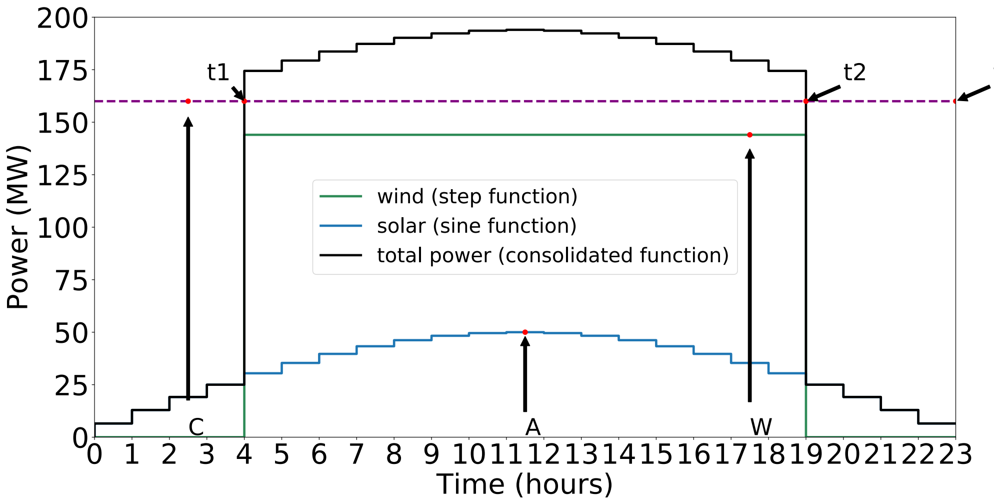


Figure 23: Input curves for solar and wind input using a simple sine- and step-function. In the figure also indicated t1, t2, t3, C, A, and W used in the function describing conservation of energy (eq.33).

The sum of the energy going into the BESS times the charge efficiency (η_{charge}) needs to be equal to the sum of the energy during discharging times the discharge efficiency ($\eta_{discharge}$).

$$\sum_{t=1}^{T} p_{in}(t) * \eta_{charge} = \sum_{t=1}^{T} p_{out}(t) * \frac{1}{\eta_{discharge}} \tag{31}$$

[with T=1..24], where π is divided in 24 steps.

In equation 32a the charging area is calculated. This is the area under the consolidated function above the physical cable capacity of the electrical infrastructure (in Figure 23 denoted as the area above the dotted purple constant line between t_1 and t_2).

$$\textbf{Charging:} \quad \eta_{in} * \int_{t_1}^{t_2} A\sin(\omega t) \quad dt \quad + \int_{t_1}^{t_2} W \quad dt \quad - \quad \int_{t_1}^{t_2} C \quad dt \tag{32a}$$

$$= \eta_{in} * \frac{A}{\omega}(\cos(\omega t_1)) - \cos(\omega t_2) + W(t_2 - t_1) - C(t_2 - t_1) \tag{32b}$$

Similar the discharging area is determined; The discharge part is the area under the cable capacity where the total power is lower than the cable capacity minus the integral of the consolidated function 32a. The exact location of t_3 is dependent on the charge, discharge efficiency, the maximum c-rate, and the 'available capacity' on the export cable.

$$\textbf{Discharging:} \quad \frac{1}{\eta_{out}} * \int_{t_2}^{t_3} A\sin(\omega t) \quad dt \quad + \int_{t_2}^{t_3} W \quad dt \quad - \quad \int_{t_2}^{t_3} C \quad dt \tag{33a}$$

$$= \frac{1}{\eta_{out}} * \frac{A}{\omega}(\cos(\omega t_2)) - \cos(\omega t_3) + W(t_3 - t_2) - C(t_3 - t_2) \tag{33b}$$

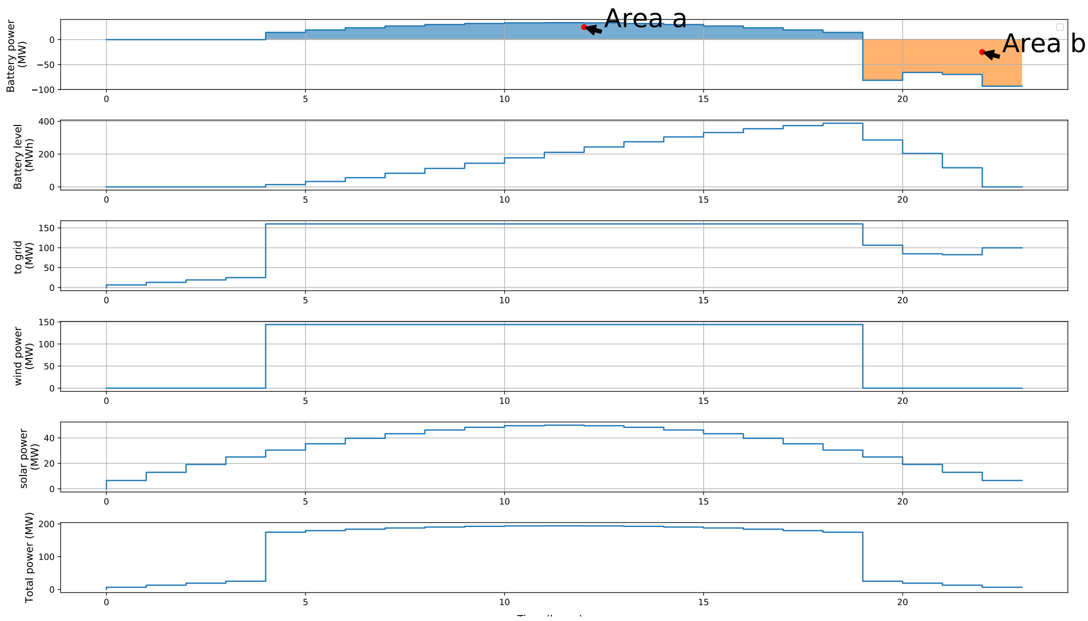


Figure 24: Sample simulation for a 24-hour period in which charging and discharging takes place. $K_{battery}$=388 MWh

Figure 24 represents the optimal result with the corresponding optimal storage size ($K_{battery}$) calculated. The used input values for the step function, sine function, and cable capacity in the analytical solution are summarized in Table 7. The optimal result is obtained for a period of 24-hour with an objective function where profit is maximized (eq. 11). In the example shown the APX price is set at a random constant value (50 Euro MWh^{-1}) to prevent the model from applying arbitrage but conserve the incentive of discharging. The charge and discharge efficiency are set at 0.98 and 0.8 respectively to show that the model is acting as intended by introducing different efficiencies.

$$\textbf{obj Function}: \sum_{t=1}^{T} P_{togrid}(t)*APX_{price}(t) - \sum_{t=1}^{T}[\rho_1 * P_{out}(t) - P_{in}(t)] - Capex, \quad \forall t \in \{1, 2, \dots T\} \tag{34}$$

Input	Value
A	50.0
W	144.0
C	160.0
t1	4
t2	19
t3	23

Table 7: Input parameters analytical verification Battery Model

To conclude, Figure 24 shows that conservation of energy is maintained (following equation 31) within the proposed Battery Model and that the algorithm act as intended. The battery size calculated by the model is similar to the size calculated by hand in Appendix E.

The conceptual Battery Model determines the storage size needed for a given location to be self-supporting and without having curtailment. In this model the size of the solar farm is 50 MWp which is sufficient to show that during peak production of both wind and solar PV the electrical infrastructure is limiting. Moreover, the electrical infrastructure (160MVA) and wind farm size (144 MWp) are also predetermined.
The model is running with an objective function where profit is maximized. The used objective function (eq. 34) is the same as used in section 5.1. The input parameters used in the Battery Model are summarized in Table 8.

Input Parameter	Value
Charge efficiency (η_{charge})	0.95
Discharge efficiency ($\eta_{discharge}$)	0.95
Battery Capex ($C_{Battery}$)	450k EUR MWh^{-1}
Solar PV farm Capex ($C_{Battery}$)	600k EUR MWp^{-1}
ρ_1	450 EUR MWh^{-1}

Table 8: Input parameters battery sub model 1

Verification by Hand

In Figure 25 the balance equation (eq.21) and battery level equation which determines when to store excess energy and how the energy is flowing have been verificated by hand to show the functioning of the proposed Battery Model. The verificated results are for 2016 full year and the figure shows a short period within the optimized result.

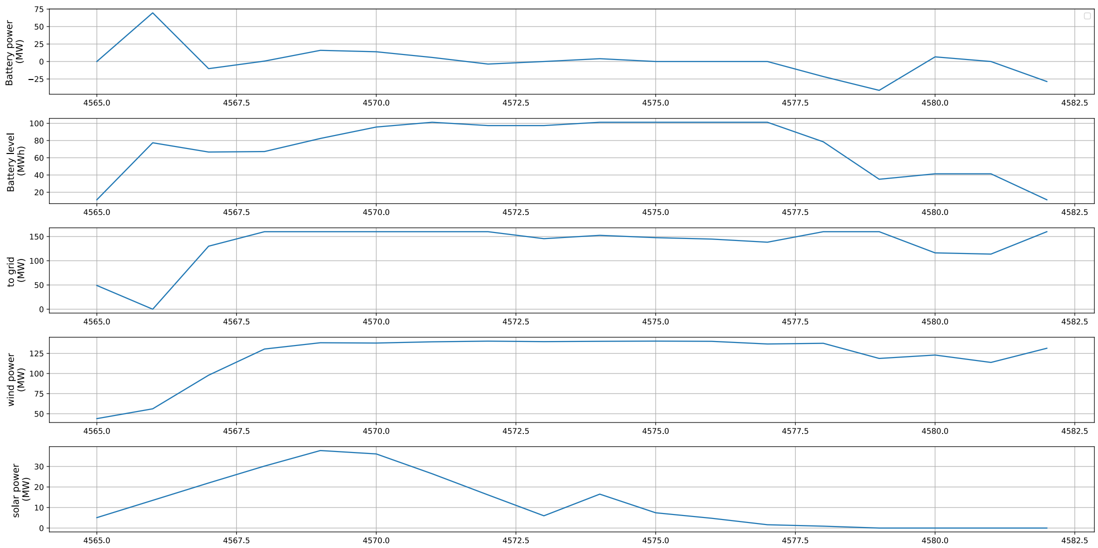


Figure 25: Overview of the Battery Model from hour 4565-4583 (18 consecutive hours). $K_{battery}$= 112 MWh & 95 MW

The Figure (25) above is showing 18 consecutive hours of sub model 1. In subplot 1 the battery power at every moment is shown. The battery plot reveals that the model is not charging and discharging at the same time. Moreover, Equation 18 is true (e.g. the upper 10% and lower 0% remain unused). In subplot 2, the energy available in the BESS is shown and corresponds with the largest period of curtailment plus an additional 20% as explained before. Subplot 3 shows the power flowing towards the grid. A positive P_{togrid} indicates that there is only elektricity flowing towards the grid (e.g. zero electricity is taken from the grid). If the model is pulling electricity, the power to the grid would be negative. Subplot 4 and 5 illustrates the power production for both the wind and solar farm at every hour.

In Table 9, the corresponding values for Figure 25 are presented.

At hour 4565, the solar and wind power combined was 49.1 (5.1 + 44.0) MW and all the energy can be transported directly to the grid (see scenario 1, Appendix C). In the coming hour the APX price is low and hence arbitrage is possible in sub model 1 the electricity will be stored to sell at a later moment in time. The exact time of hour 4566 is at 6 am where the optimizer is able to fill the battery with solar and wind power instead of selling to the grid directly. In hour 4567, 10.2 MW is sold to the grid, next to the solar and wind production of that hour. In the coming hours, 4568 till 4571 the electrical infrastructure is limiting and thus all the excess energy needs to be stored. The surplus energy is flowing in the BESS resulting in a total battery level (E_B) of 101.2 at the end of hour 4571. When there is available capacity on the export cable energy can flow from the BESS towards the grid. This can be seen in hour 4572, the discharge efficiency is used to transport the maximum amount of power over the cable during that hour (160.0). During peak APX prices which is around 6/7/8 pm the conceptual model is discharging as much power as there is capacity available (hour 4578 & 4579). At hour 4582, the battery is discharged untill the lower discharging limit (E_{B-}).

Index(hour)	$P_{batt}(t)$	$E_B(t)$	$P_{togrid}(t)$	$P_{solar}(t)$	$P_{wind}(t)$	APX(t)
4565	0.0	11.2	49.0	5.1	44.0	22.5
4566	69.6	77.4	0.0	13.5	56.1	20.2
4567	-10.2	66.6	130.1	22.0	97.9	22.8
4568	0.6	67.2	160.0	30.2	130.4	25.2
4569	16.0	82.4	160.0	37.8	138.2	29.3
4570	14.0	95.7	160.0	36.1	137.8	36.0
4571	5.8	101.2	160.0	26.4	139.4	36.8
4572	-3.6	97.4	160.0	16.1	140.2	28.6
4573	0.0	97.4	145.6	6.0	139.6	22.4
4574	4.0	101.2	152.5	16.5	140.0	21.9
4575	0.0	101.2	147.7	7.4	140.2	27.1
4576	-0.0	101.2	144.7	4.8	140.0	32.2
4577	-0.0	101.2	138.3	1.6	136.7	33.0
4578	-21.5	78.5	160.0	0.9	137.5	36.0
4579	-41.3	35.1.4	160.0	0.0	118.7	35.3
4580	6.7	41.4	116.3	0.0	122.9	31.5
4581	-0.0	41.4	113.8	0.0	113.8	34.1
4582	-28.6	11.2	160.0	0.0	131.4	37.4
4583	0.0	11.2	108.7	0.0	108.7	26.3

Table 9: Verification of the Battery Model, step-by-step with arbitrage. For 19 consecutive hours in 2016. The numbers are rounded at 1 decimal for this example and discharge and charge efficiencies are set at 0.95.

Since the battery is only used for prevention of curtailment and for self consumption during periods of no wind nor solar power production the minimum battery size ($K_{battery}$) needed will be roughly the same number as the largest period of curtailment in this simulated time series plus (η, E_B^+, and E_{B-}). This is, for the year 2016, at the 19th of July at 12:00 am till 18:00 pm. Due to the limiting electrical infrastructure 95.5 MWh needs to be stored. After some charge, discharge losses, and upper and lower charging limits the optimal battery size ($K_{battery}$) found is 112 MWh & 95 MW (maximum value P_{batt}, see Figure 26).

Overview Battery Model

The optimal behavior of the BESS is visualised in figure 26. The exact value from the data behind the figure presented is stated in Table 8. The model is able to find the optimal battery size as described in the third sub-objective. As previously mentioned, it can also be seen that the upper and lower 10% of the battery level remain undrawn.

Optimization results Battery Model (range: hour 4000-6000, 2016)

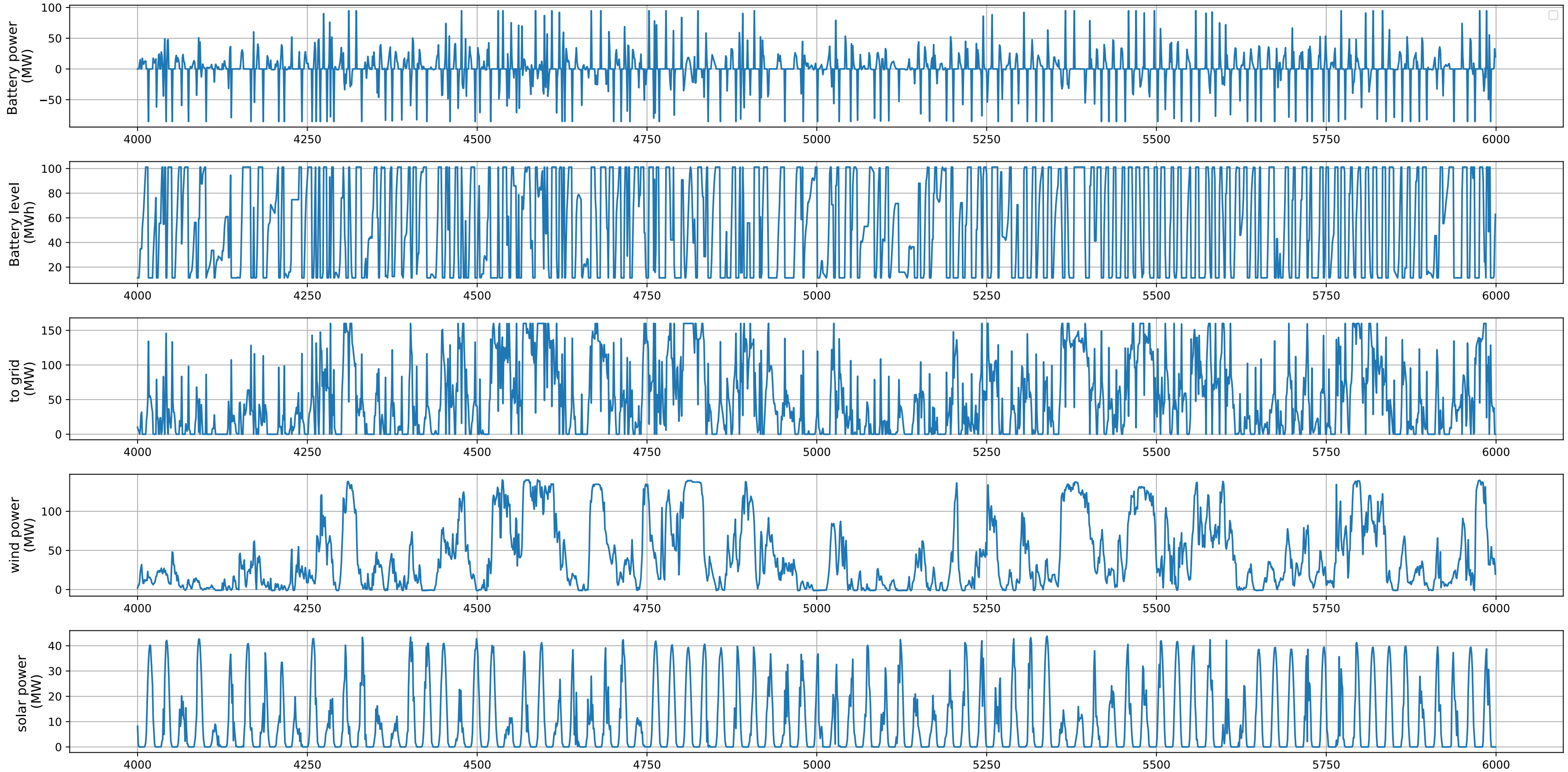


Figure 26: Overview Battery Model: Battery Power, Battery level, Power to grid, Real Wind power, and Simulated Solar power. K_{battery} = 112 MWh & 95 MW.

5.2 Prevention of Imbalance

The aim of the imbalance model is to look for the optimal battery capacity (in MWh) while reducing the imbalance exerted by the wind farm. The model is the same as the battery model, but another input parameters is needed. The imbalance time serie as explained in section 2.4 is the amount of power there is produced more or less than forecasted the day before. As explained in the fourth sub-objective of this study a more reliable generation profile is preferable. Ever since, the first outcome of the model is looking for the optimal outcome of the objective function (maximizing profit) but now by minimizing exerted imbalance (if economically feasible).

As described in equation 35 the imbalance model tries to minimize the imbalance (if feasible). The prior is done by introducing a tracking problem method in which imbalance is penalized. The exact 'weight' or 'additional value' of minimizing imbalance is for each wind farm and year different. The alpha factor within the objective function can be manually chosen and is responsible for the amount of imbalance filtered by the BESS. For now alpha is set at 4 EUR/MWh^2. A method for determining the actual value of imbalance is explained in Appendix E.

$$-\alpha * \sum_{t=1}^{T}(-P_{out}(t) + P_{in}(t) - P_{imbalance}(t))^2 \tag{35}$$

Where $\mathrm{P}_{\mathrm{imbalance}}$ is positive when there is more produced than forecasted and negative when there is less produced than forecasted. In the imbalance model the real wind generation profile along with the imbalance profile are used as input variables over time. The BESS algorithm will minimize imbalance in periods when the combination of $\mathrm{P}_{\mathrm{wind}}$ and $\mathrm{P}_{\mathrm{solar}}$ is lower than the cable capacity. In the Imbalance Model storing excess energy is prioritised first, e.g. the BESS will minimize the imbalance in periods when the combination of $\mathrm{P}_{\mathrm{wind}}$ and $\mathrm{P}_{\mathrm{solar}}$ is lower than the cable capacity.

5.2.1 Analytical Verification Imbalance Model

Figure 27 gives an overview of the simplified input for the verification of the imbalance model, where imbalance can be minimized (if economically feasible). Verification of the algorithm is performed by controlling and checking the variables for every hour for scenarios in which the outcome can be predicted. The conceptual model is considered to be correctly when the deviation is insignificant from the expected behavior. The key function of the BESS is to prevent curtailment first. Thereafter the model is checking if decreasing the amount of imbalance exerted is economically viable.

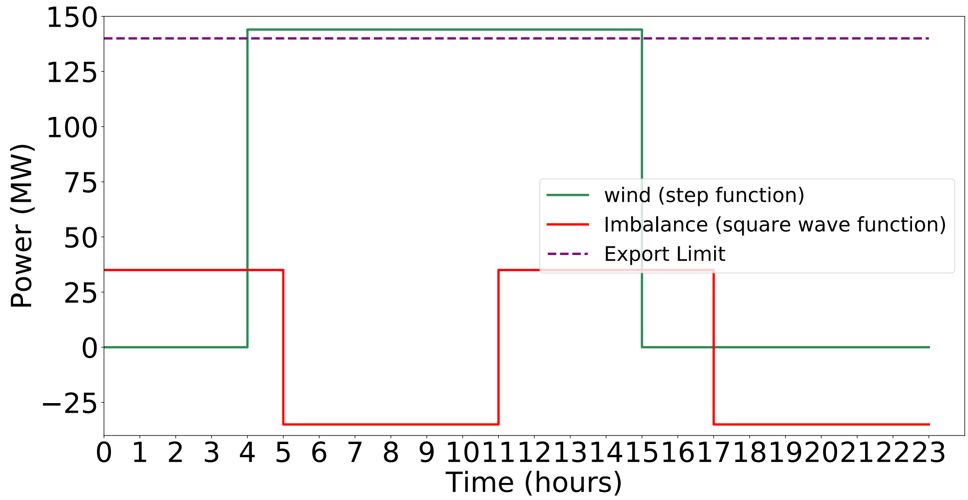


Figure 27: Input curves for wind and imbalance input using a simple square wave and step-function. Export limit = 140 MVA, Wind step-function as in eq. 29, and Imbalance square wave function (+35 and -35 MW).

Verification of the model is performed by using an extreme case in which minimizing imbalance is extremely important. For the wind input a similar step-function has been used as in section 5.1. Wind power is constant 144 MW from the fourth hour untill the fifteenth hour. The export limit has been set at 140 MVA to show that during peak production not all the power can be transported (limiting electrical infrastructure) but the excess part needs to be stored (prioritised first). A square-wave function has been used to show the random behaviour of imbalance.

Execution of the algorithm (imbalance) for a period of 24 hours leads to the results presented in Figure 28. This figure shows an extreme case in which the outcome can be predicted. A penalty of 1.0 e^9 Euro MWh^{-1} squared is given for every MWh of imbalance.

Please note that the solar power output is set at zero and the APX price is constant to prevent the model from applying arbitrage in this verification for simplicity.

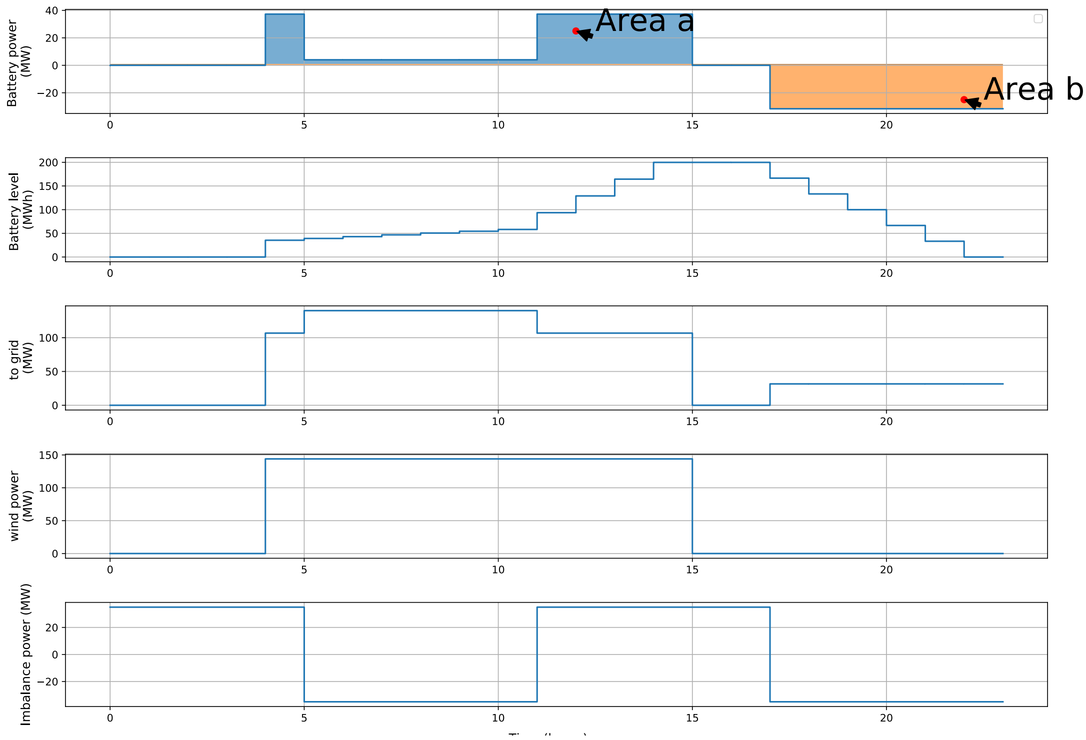


Figure 28: Sample simulation for a 24-hour period in which the behaviour can be predicted. $K_{battery}$=200 MWh & 37 MW.

The purpose of this verification is showing that the model acts as designed. As an example, the events that occur are visualised in Figure (28) and for consistency also presented in Table (10). The first hours the battery is unloaded. The production by wind is zero therefore the production cannot be lowered to minimize imbalance by wind. At hour 5, there is a positive imbalance and the wind production to the grid is lowered and a part is fed into the BESS. During a production higher than the cable capacity the excess energy is stored because this is prioritised first. The negative imbalance cannot be decreased since the cable limit is reached. According to the imbalance equation (35) the positive imbalance forces the model to enlarge the battery and store this energy. In case of no wind power production and a positive imbalance, nothing happens (taking electricity from the grid is not allowed 21). Afterwards the model is discharging untill the energy level is at zero as long as there is a negative imbalance.
After the introduction of a BESS the MAE is decreased from 35MW to 21MW (60%) in this example.

Index(hour)	$P_{batt}(t)$	$E_B(t)$	$P_{togrid}(t)$	$P_{wind}(t)$	$P_{imbalance}(t)$
0	0.0	0.0	0.0	0.0	35.0
1	0.0	0.0	0.0	0.0	35.0
2	0.0	0.0	0.0	0.0	35.0
3	0.0	0.0	0.0	0.0	35.0
4	0.0	0.0	0.0	0.0	35.0
5	37.3	35.4	106.7	144.0	35.0
6	4.0	39.2	140.0	144.0	-35.0
7	4.0	43.0	140.0	144.0	-35.0
8	4.0	46.8	140.0	144.0	-35.0
9	4.0	50.6	140.0	144.0	-35.0
10	4.0	54.4	140.0	144.0	-35.0
11	4.0	58.2	140.0	144.0	-35.0
12	37.3	93.6	106.7	144.0	35.0
13	37.3	129.0	106.7	144.0	35.0
14	37.3	164.4	106.7	144.0	35.0
15	37.3	199.8	106.7	144.0	35.0
16	0.0	199.8	0.0	0.0	35.0
17	0.0	199.8	0.0	0.0	35.0
18	-31.6	166.5	31.6	0.0	-35.0
19	-31.6	133.2	31.6	0.0	-35.0
20	-31.6	99.9	31.6	0.0	-35.0
21	-31.6	66.6	31.6	0.0	-35.0
22	-31.6	33.3	31.6	0.0	-35.0
23	-31.6	0.0	31.6	0.0	-35.0

Table 10: Verification of the Imbalance Model step-by-step for 24 consecutive hours. In this example, the numbers are rounded at 1 decimal and discharge and charge efficiencies are set at 0.95.

To conclude, the algorithm presented is capable of storing excess energy during grid connection capacity limitations, being self-sufficient, and maintain conservation of energy. The algorithm is able to minimize imbalance if economically feasible. It is established that the proposed model minimizes imbalance by a penalty factor alpha. This factor can be adjusted by altering the objective function.

5.3 Optimal Solar PV Farm Sizing

The presented Battery PV model is able to determine the optimal solar PV farm size (MWp) while also calculating the optimal BESS size (MWh MW^{-1}). In the previous Battery and Imbalance Model an approximated size (based on the Curtailment analysis, section 3.1) is chosen which was sufficient to show that during peak production of both wind and solar PV the electrical infrastructure was limiting. Curtailed energy was not allowed. (e.g. all the energy which is generated is used). In this model however, curtailing energy is allowed (see section 4.5).

Basically, the presented model is able to look for the optimal configuration (sizing) of adding a solar PV farm and BESS system to an existing wind farm. In this model the trade-off between a BESS and a solar farm can be calculated (i.e. the additional gain of installing an extra MWp of solar and curtailing this energy or storing in the battery system during peak production).
The model is able to calculate the profit for every possible size (see equation 14), where every (extra) MWp installed capacity should result in a higher profit. The proposed model is able to curtail solar power as stated in equation 26 as long as this will result in a more financially feasible outcome.

5.3.1 Analytical Verification Battery PV Model

The presented Battery PV Model is verificated by means of increasing the capex parameter of both the solar PV farm and the BESS (C_{solar} and $C_{battery}$) by a factor 10. Since the underlying algorithm is able to curtail a certain percentage of the obtainable solar energy, the outcome is hard to predict.

The simulation scenarios are:

1. Extremely cheap solar PV farm;
2. Extremely cheap BESS;
3. Normal prices;

Hypothesis scenario 1; With extreme low solar installations costs, the algorithm must return a battery size of zero and a large solar farm (K_{solar}).
Hypothesis scenario 2; The algorithm must return an excessively large BESS when the battery installation cost is ten times lower than in reality (solar farm installation cost is unaltered).
Hypothesis scenario 3; A large solar PV farm and no BESS.

Scenario	Capex PV farm	Capex BESS	$K_{battery}$	K_{solar}	perc. curt. solar AEP
1	65e3	5e5	0.0 MWh	1226 MWp	92%
2	65e4	5e4	584 MWh	67 MWp	0.0%
3	65e4	5e5	0.0 MWh	320 MWp	78%

Table 11: Verification results of the Battery PV Model for a 24-hour input in which the behaviour can be predicted. Export limit = 160 MVA, Wind step-function as in eq. 29. Discharge and charge efficiencies are set at 0.95.

The results of these three scenarios are shown in Table 11. The hypothesis for scenario 1, where the installation cost of solar PV is a factor ten lower results in a very large optimal solar farm size as expected. In this configuration storing electricity is more expensive then curtailing during peak production of both wind and solar. Hence, the optimal size of the BESS is zero. In scenario 2, the capex of the BESS is lowered by a factor 10. The optimal battery size found is 584 MWh and corresponds to the hypothesis. Since curtailed solar energy is allowed and there is capacity available on the export cable the optimal solution states that a solar farm of 67 MWp installed capacity will result in the maximum obtainable profit. In this solution no solar energy is curtailed and therefore this outcome seems correct. In the third scenario, where normal prices are used results in a set-up with a solar PV farm of 320 MWp. In this result no BESS is present. A possible explanation for this result; the additional gain of applying arbitrage is not significant in the (analytical) verification shown due to the limited amount of time-frames and lack in price differences where storage can be financially worthwhile.

5.4 Sensitivity Analysis

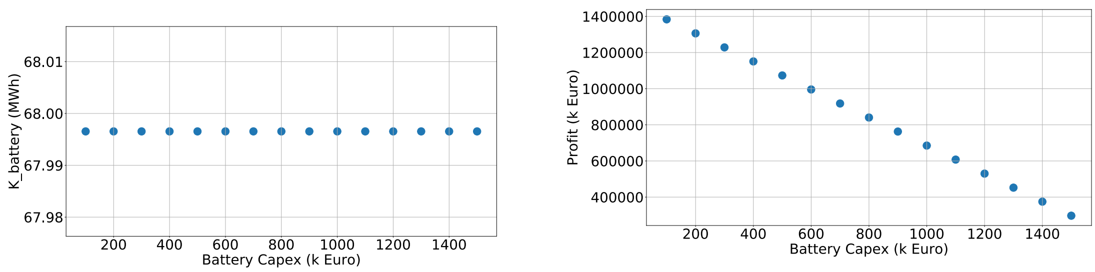
In this chapter, the behaviour of the conceptual model is described. Several sensitivity analyses are conducted to evaluate the performance of the different optimization models. Relevant simulation parameters will be identified in order to quantify the impacts of changing them. All simulations carried out for the sensitivity analysis were performed on the wind, solar, price, and forecast input data for the period 01-01-2016 untill 31-12-2016. Multiple prediction findings were computed and are presented.

The simulation parameters used for assessment are:

- Battery Capex [Euro MWh^{-1}]
- Solar PV farm Capex [Euro MWp^{-1}]
- alpha (α) factor; penalty factor imbalance [EUR/ MWh^2]
- MAE [% to nominal capacity]
- Profit; outcome objective function [Euro]

5.4.1 Battery Model

It has become apparent that simulation of battery model 1 results in an optimal battery size ($K_{battery}$) which is determined by the longest period that energy cannot be transported to the grid. Varying the battery installation cost ($C_{battery}$) could possibly result in a size exceeding the longest period of curtailment. Since the problem is completely linear, the optimal battery capacity found must scale linear with battery Capex.



(a) Optimal battery sizing ($K_{battery}$) as a function of Battery Capex.

(b) Outcome objective function (maximize profit) as a function of Battery Capex.

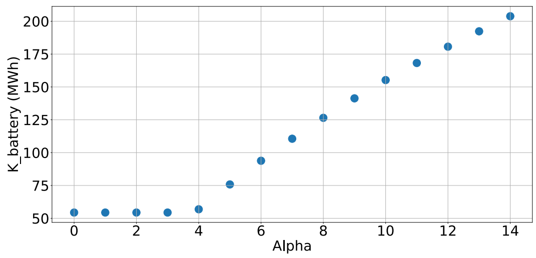
Figure 29: Sensitivity Analysis Battery Model: η_{charge} = 0.95 & $\eta_{discharge}$ = 0.95, C_{solar}=650k EUR MWp^{-1}.

Based on the results presented in Figure 29 the installation cost of the BESS does not change the optimal battery size. Following the results presented the hypothesis of a linear behaviour is fully confirmed. The optimization problem uses the objective function as stated in equation 34. Furthermore, it can be concluded that applying arbitrage, storing excess energy, and being self-sufficient alone is not sufficient for the algorithm to install a larger BESS.

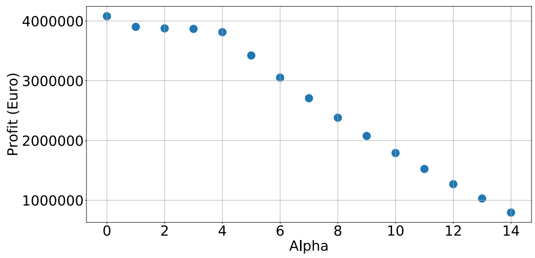
5.4.2 Imbalance Model

A sensitivity analysis regarding determining the optimal storage size and minimizing imbalance is performed. Since the underlying model of the optimization algorithm is non-linear, the optimal battery capacity and behavior is hard to predict.

The performed analysis is shown in Figure 30 and Figure 31. The optimal battery size is studied by varying the imbalance penalty. In the same analysis the outcome of the objective function as well as the increase in being more in line with forecasted production is studied. The results of penalizing imbalance by an alpha in the range from 0-14 EUR/MWh^2 is shown below.



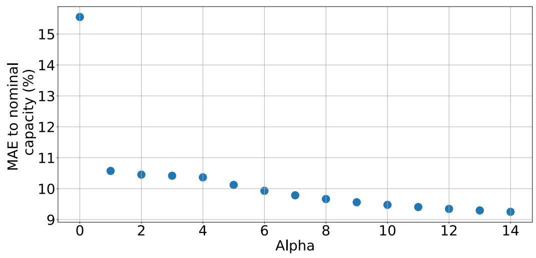
(a) Correlation between alpha and optimal battery size($K_{battery}$).



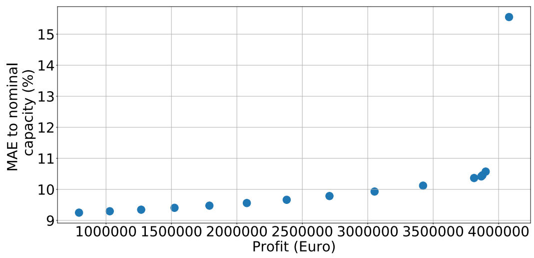
(b) Correlation between alpha and outcome objective function (maximize profit).

Figure 30: Sensitivity Analysis of Sub Model 2: $\eta_{charge} = 0.95$ & $\eta_{discharge} = 0.95$. $C_{battery}$ = 450k EUR MWh^{-1} & C_{solar} = 600k EUR MWp^{-1}.

Looking at the results of Figure 30 of minimizing imbalance, two distinctive trends can be seen. First, the overall profit of the system will be lower as the imbalance penalty factor is increased (Fig. 30b). By effectively penalizing imbalance by a higher alpha, the optimal battery size is also constantly increasing. The minimum battery size needed is around 54 MWh and by applying a higher penalty this size increases almost completely linear. Likewise the profit of the system decreases when imbalance is penalized harder.



(a) Correlation between alpha and MAE (% to nominal capacity).



(b) Correlation between MAE (% to nominal capacity) and outcome objective function (maximize profit).

Figure 31: Sensitivity Analysis of Sub Model 2: $\eta_{charge} = 0.95$ & $\eta_{discharge} = 0.95$. $C_{battery}$ = 450k EUR MWh^{-1} & C_{solar} = 600k EUR MWp^{-1}.

In Figure 31 the MAE is plotted as a function of alpha and as a function of the outcome of the objective function (where profit is maximized, eq 24a). By applying a higher penalty factor the initial MAE which is specific for this wind farm and therefore used data decreases from ±12% without any incentive to minimize imbalance to 9% at an alpha of 14 EUR/MWh^2. Note that the MAE at an alpha of zero is higher (than initially) due to the fact that the model is able to apply arbitrage. Without penalizing imbalance the model is applying arbitrage causing more deviation from the forecast. Figure 31a demonstrates that the MAE decreases by applying a higher penalty.
Figure 31b reveals that minimizing imbalance here is not increasing the outcome of the objective

function. From the results presented one can conclude that by applying a higher penalty (α) there is a decrease in profit.

5.4.3 Battery PV Model

In the third battery sub model, the algorithm should be able to determine the optimal BESS size and solar PV farm size in a single run. Figure 32 & 33 represents the changes in configuration when a higher Battery Capex or Solar PV farm Capex is applied. Since cost is the main decission factor in this sizing study, the trend of a smaller battery size is expected by an increasing battery price. Parallel, the size of the solar PV farm is expected to decrease with increasing cost. The difficulty in this model lies in the ability of curtailing solar power versus storing or transporting solar power via the export cable. Note: the sensitivity carried out is for 2000 consecutive hours in 2016 (hour 2000-4000).

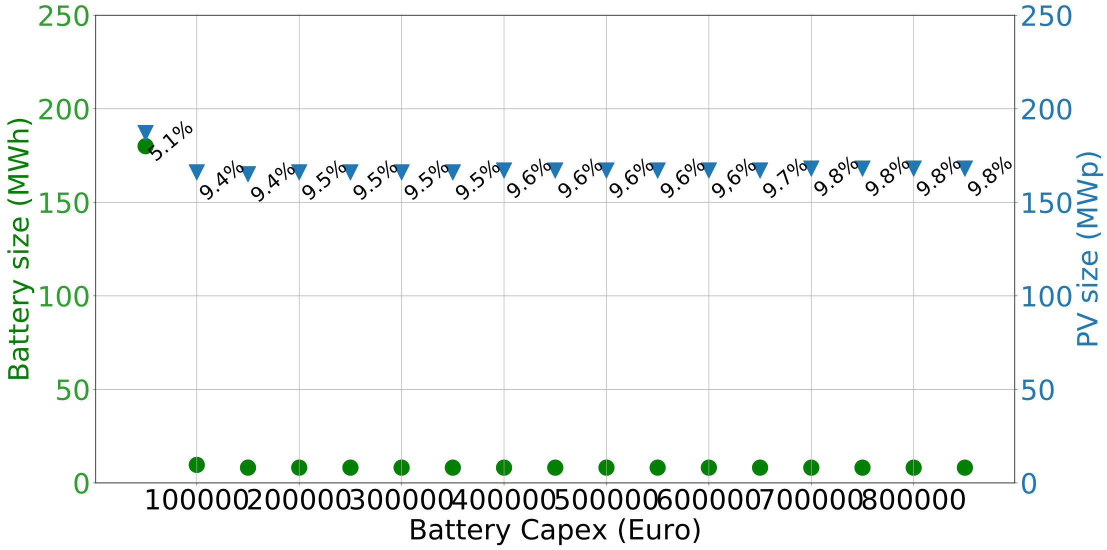


Figure 32: Optimal sizing as a function of Battery Capex. $\eta_{charge} = 0.95$ & $\eta_{discharge} = 0.95$. C_{solar} = 520k EUR MWh^{-1}. (% Curtailed solar AEP plotted on bullets)

The results of a varying Battery Capex and the outcome after iterating the Battery PV Model are presented in Figure 32. Note that the expected trend can differ from the outcome presented due to the ability to curtail the solar power. For all the iterations the amount of curtailed solar power with respect to AEP is depicted at the bullet points. Execution of the algorithm in Figure 32 is carried out with a conservative solar capex of 520K EUR MWp^{-1}. The results demonstrates that within this range of battery installation costs and by using the BESS only for self-consumption, arbitrage on the APX market, and the ability to store excess energy the cost of installation does not influence the sizing for this specific case.

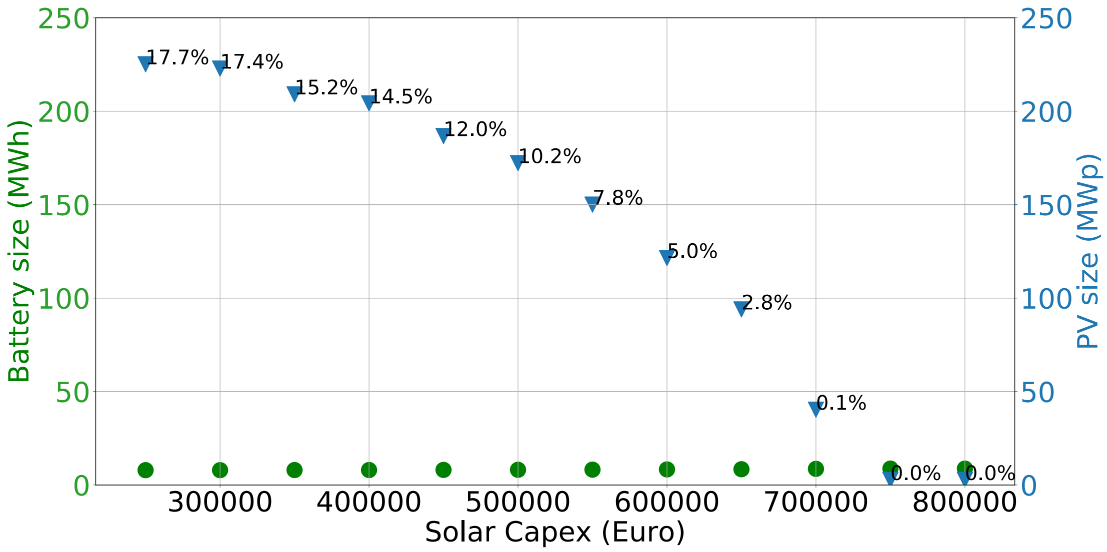


Figure 33: Optimal sizing as a function of Solar Capex. $\eta_{charge} = 0.95$ & $\eta_{discharge} = 0.95$. $C_{battery}$ = 450k EUR MWh^{-1}. (% Curtailed solar AEP plotted on bullets)

Figure 33 represents the trend in sizing with a varying solar PV farm installation cost. Simulation of the optimization algorithm has once again been performed for each individual Solar PV Capex. All iterations carried out using a constant (conservative) battery Capex of 450k EUR MWh^{-1}. From the above graphs it can be concluded that the solar Capex of the sustainable power station makes a huge impact on the configuration as can be seen in the graphs shown. This graphs does also show that the percentage curtailed solar AEP differs for every configuration. The scenario with the highest percentage of curtailed solar energy is around ±18% and seems at the limit for a healthy solar business case (considering the benefits of sharing a grid connection, and transformer according to market experts from Ventolines B.V.).

However due to the uncertainty and lack of runs (due to limited computational speed) over a period of multiple years no significant conclusions on the performance of this last battery model can be drawn. Potentially, using a faster non-linear solver will make a difference in the computation of these optimization problems. However, the simulation results for this solar PV installation cost show that significant overplanting is (sometimes) the most economically profitable. Here, the storage system is only used for self-consumption, applying arbitrage on the APX market, and ability to store excess energy. Allowing the battery to trade directly on the imbalance market and FCR market. By using the BESS differently the optimal configuration might be different.

5.5 Summary and Conclusion

In this chapter, three dynamic simulation models has been developed for assessment of a grid connected sustainable power station in a liberalised western electricity network. The model built focusses on the Dutch market, but is applicable to most western European countries. First, the different models have been verificated analytically and extended with illustrations. It was concluded that conservation of energy was true and that each model acts as intended. The Imbalance Model developed in this chapter incorporates a tool which is able to penalize imbalance by a factor which is in line with the cost of imbalance estimated by market parties. Furthermore, the tool developed is able to apply arbitrage and look for the optimal outcome and corresponding battery size when the principle of zero curtailment is valid. In the last battery PV model, The algorithm presented is able to look for the optimal battery size and optimal solar PV farm size in a single run. Here, curtailing of solar power is allowed. From the results presented in section 5.4.3 can be concluded that with current battery prices it is not feasible to install a larger BESS than only for self-consumption.

Sensitivity Analysis
Morover, an extensive sensitivity analysis has been carried out. The proposed Battery Model demonstrates that the battery Capex did not influence the optimal battery size, unless prices are ten times lower than today. The optimal battery size computed is approximately large enough to absorb all the energy during the longest period of curtailment (since no curtailment is allowed). By using the battery only for storing excess energy, applying arbitrage on the APX market, and for self-consumption the size did not exceed this minimum size needed. In the Imbalance Model, the exerted wind power imbalance can be minimized by introducing a penalty for every MWh imbalance. From the simulation set-up and results, it is concluded that minimizing imbalance is economically not feasible in this way. A minor decrease in MAE results in a significant decrease in profit.
The simulation results for the Battery PV Model varied considerably. The change in installation cost for the solar PV farm demonstrates a distinctive trend where at lower costs more solar energy is optimal, and also a higher level of curtailed solar power is preferable. The sizing of the battery storage system does not change significantly with the change in Capex of both the storage system and solar PV farm.

6 Simulation Results & Case Study

This chapter contains the results of the proposed models imposed on the situation of the Westermeerwind wind farm for the years 2016, 2017, and 2018. The results of Westermeerwind will be presented following current price scenarios and input parameters in line with the actual situation of Westermeerwind. Naturally, depending on the simulated year (wind and solar availability) and used input parameters the results will vary but can act as a fair indication.

The search for the most cost-effective configuration is cut in pieces where every battery service and assumption is analyzed individually:
First, the Battery Model is presented where the value of being self-sufficient, reducing grid costs, prevention of curtailment, and applying energy storage arbitrage is described when multiple solar PV farm sizes are incorporated to the Westermeerwind grid connection. Secondly, the imbalance model is used to verify what would happen in terms of sizing and profit when self-inflicted imbalance is reduced by the BESS. The imbalance value corresponding to the year of production is used as an input parameter. Thirdly, the Battery PV Model is used to calculate what the optimal configuration in terms of BESS sizing and solar PV farm sizing is when curtailing of solar energy is allowed.

Figure 34 is an aerial photograph of the (sub)shore wind farm studied. In the Figure a visualisation is presented of where the solar PV farm might arises.

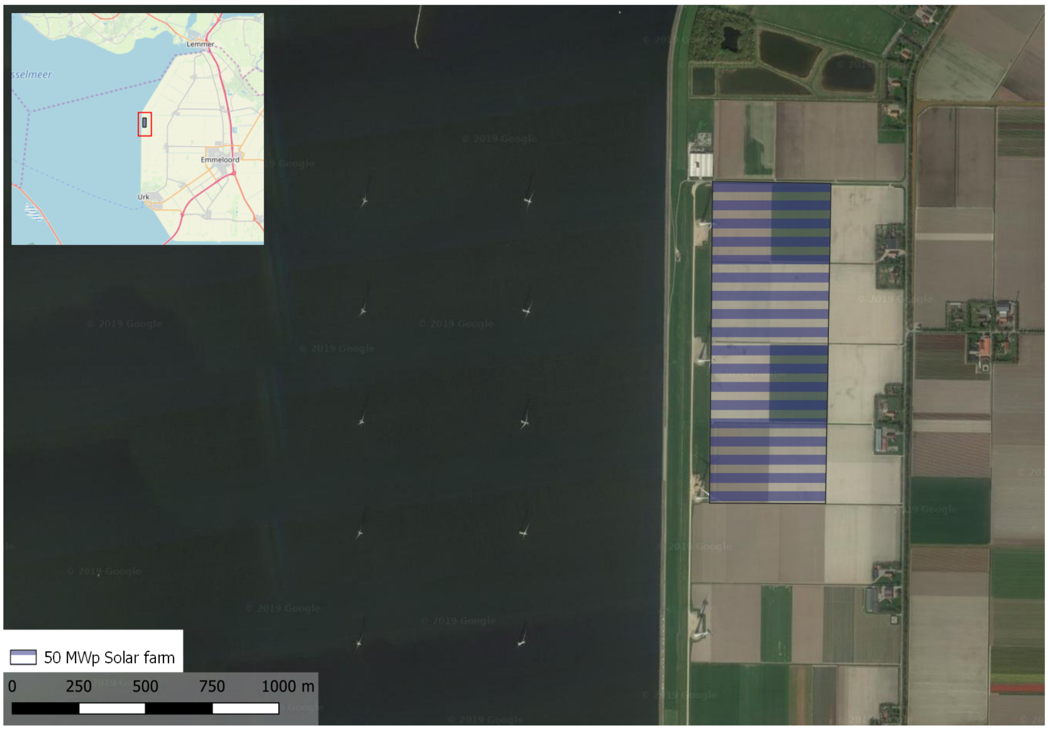


Figure 34: Visualisation of the addition of a 50 MWp solar farm to the existing Westermeerwind wind farm.

Load Data

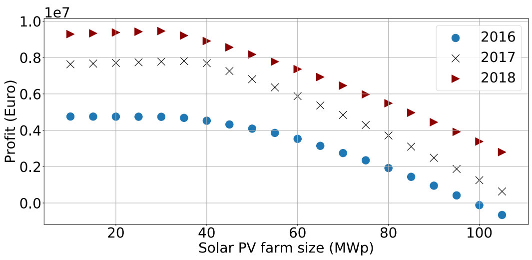
Realistic generation profiles are essential in ensuring a worthy case study. In the coming analysis measured wind power data, measured wind farm consumption data, 24-hour ahead forecasts, and apx price data has been used. Due to the lack of publicly available solar PV production data this analysis combines the Meteosat solar profile for 2016 combined with the generation output of Westermeerwind. As explained in section 2.1, solar power is much more constant over the years than wind generation data (e.g. AEP is more constant) and seems therefore accurate.

Input Parameters

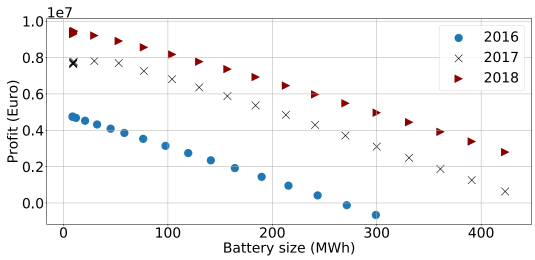
For the algorithm the following market prices are used. The price of installation for a 10-100 MWp solar PV farm is estimated at ±560k EUR MWp^{-1}. Analyses of different financial models of solar PV farms (Ventolines B.V.) revealed that the grid connection makes up 7 to 11 percent of the total capex. The total capex is therefore taken 7% lower which comes down to a capex of 520k EUR MWp^{-1}. For the battery capex, 10% of the total installation cost can be cut when the crane lifting place and grid connection can be used. Therefore a capex of 450k EUR MWh^{-1} is assumed.

6.1 Simulation Results Battery Model

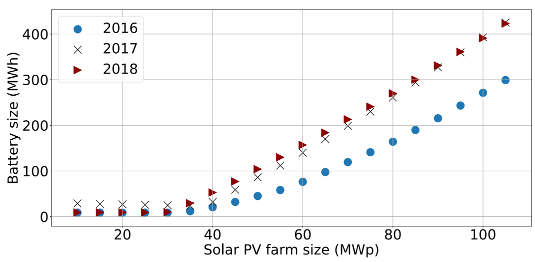
The results based on the APX price, production data, consumption data, and the simulated solar output for the years 2016, 2017, and 2018 are summarized in Figure 35.



(a) Profit sustainable power station as a function of solar PV farm size.



(b) Profit sustainable power station as a function of battery size.



(c) Battery size as a function of solar PV farm size.

Figure 35: Results Battery Model: $\eta_{charge} = 0.95$ & $\eta_{discharge} = 0.95$, C_{solar}=520k EUR MWp^{-1}, $C_{battery}$=450k EUR MWh^{-1}, C_{wind}=900k EUR MWp^{-1}.

Note that the wind production for 2016 is substantially lower than 2017 and 2018. This is due to that the last wind turbine became operational in June. The Westermeerwind wind farm is built at the end of 2015 and first months of 2016. The wind AEP for 2016 is 394 GWh, for 2017 506 GWh, and for 2018 463 GWh.

Figure 35a indicates that with increasing solar PV farm size, the outcome of the objective function will increase till an optimum around 30 MWp. Installation of a larger solar PV farm results in a lower profit. The cost of installation is too substantial to overcome with current prices. The corresponding battery size needed to be self-sufficient here is ±10 MWh. Figure 35c illustrates that the battery size needed linearly increases when the combined generation peaks above the cable capacity.

It can be concluded that with current prices (electricity price and installation costs of RES) the overall profit of the system decreases with installing a larger BESS and solar PV farm than the optimum presented here. The marginal gain of each battery service of the conceptual Battery Model is therefore analysed in more detail. In the coming sections the value of storing excess energy (6.1.1) and sharing a grid connection (6.1.2) is investigated.

6.1.1 Storage of Excess Energy

Excess energy is the energy what needs to be stored during peak production of both wind and solar PV when the electrical infrastructure is limiting. Hereby curtailment is prevented. In this study when we speak about curtailing, we mean tweaking the generation of the wind farm and or solar PV farm enabling that the combined generation can be transported to the grid. By introducing a BESS connected to an existing wind farm in combination with a solar PV farm this energy does not necessarily have to be curtailed. The value of storing this so-called excess energy can be determined by understanding the price a RES owner receives for every MWh produced. In the next paragraph this will be explained by introducing the Dutch subsidy climate for renewable energy generation.

Market Price Plus Subsidy

The optimization algorithm uses a variable APX price as a base-case, however most wind farms which are now in operation are subsidized by a so called subsidy regime called Stimulation of Sustainable Energy Production (in Dutch: Stimulering Duurzame Energieproductie) (SDE). In the Netherlands there is one budget for all sustainable energy production categories. An applicant can apply for subsidy up to a maximum base amount per MWh for each technology. When the applicant is able to produce energy for this base amount or less, the applicant can apply for subsidy. Those that apply for the lowest base amount are granted subsidy first. For those applying for the same base amount, subsidy is granted on a first come, first serve, basis.

The subsidy act as a capped feed-in-tariff: for each MWh produced, the average spot price is increased to the Market price plus subsidy (SDE price). The subsidy is the SDE price minus the market price. However, if the market price is below a floor price, only the difference between the SDE price and floor price is paid. This means there is a certain 'gap' in this support mechanism. When the market price is at or above the floor price, the project receives the higher of the market price and the SDE price. The subsidy is granted for 15 years, following full commissioning of the Project.

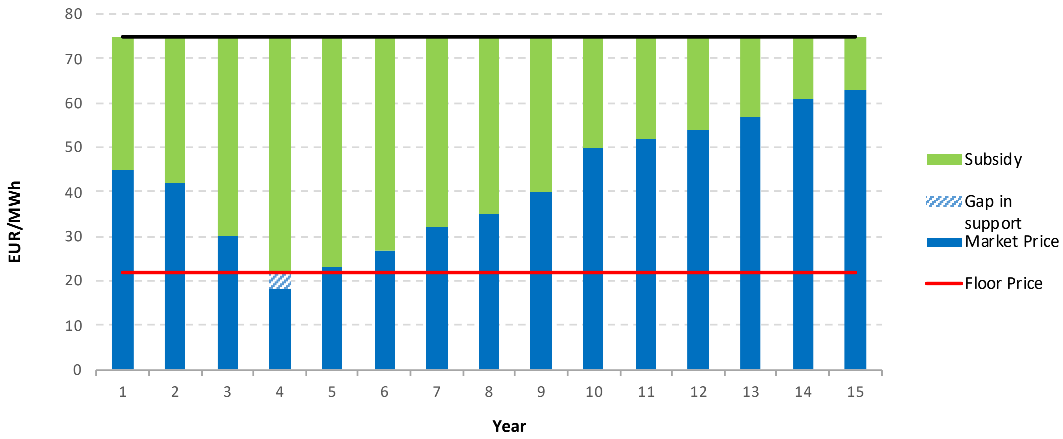


Figure 36: Example calculation of Dutch subsidy regime.

Figure 36 represents the Dutch subsidy regime for a potential solar PV farm with an SDE price of 75 EUR MWh^{-1}.

The algorithm in the Battery Model uses the energy discharged times the APX price as the value of storing excess energy. However, the true value is slightly higher than modelled. Market parties receive the SDE price (Market price plus Subsidy) times the energy which is stored instead of curtailed. Dependent on the percentage of solar AEP which needs to be curtailed this can become a meaning full source of income for the sustainable power station.

6.1.2 Cable Pooling

Sharing a grid connection and forcing the sustainable power station being self-sufficient does also has value. By introducing the concept that no power is extracted from the grid at all times the sustainable power station itself will be able to foresee in the electricity needed for the wind farm at periods that the generation is not sufficient. Yawing a wind turbine cost for a short period of time a lot of power. The value of being self-sufficient is not in the amount of energy which is used for self-consumption but there is a different financial benefit instead. Westermeerwind is connected to the High voltage grid (110kV) and therefore does not pay for transport as a service. The dutch TSO, Tennet only charges Westermeerwind for a monthly connection fee and transmission fee. The charge for absorbing electricity from the grid was for the year 2018 around 30k Euro. This cost is based on the peak consumption per month that Westermeerwind have had in 2018.

A second incentive for cable pooling is that there is no need for an expensive grid-connection. The cost of a grid connection for a solar PV farm in the Netherlands is extremely project specific and can therefore not be calculated explicit. Typically, the cost for a grid-connection is determined by the capacity and length of the cable towards the grid operator. For the case study of Westermeerwind it is assumed that no new investment is needed and the back-up transformer can be used for the sustainable power station.
Analyzes of financial models of solar farms in the size range 10 - 100 MWp, indicates that the average grid-connection cost with respect to the total installation cost is 7 to 11 percent. The savings on grid connection cost has been applied on the used input parameters ($C_{battery}$ & C_{solar}). Besides the cost which can be spared, is cable pooling also an important way of building new RES while a lot of zones in the Netherlands are marked as red, where zero new grid-connections are disclosed.

From the simulation set-up and results of the Battery Model imposed on Westermeerwind it is optimal to install a solar farm of ±30 MWp in combination with a BESS of 10 MWh. Yet, the optimal configuration determined by the Battery Model is strongly dependent on the availability of solar and wind, simultaneity of resources, and electricity prices. From the analysis presented one can notice that installation of a larger solar PV farm results in peak production above cable capacity. The decreasing trend in profit indicates that setting-up a larger storage system with current battery capex and spread on the apx market is not feasible.

6.2 Imbalance Model

In this section the Imbalance Model is used to explore the configuration of a potential sustainable power station which is more reliable. The average value of every MWh of imbalance for Westermeerwind is computed following the rules published by RVO (Rijksdienst voor Ondernemend Nederland) and uses the settlement (long and short) prices published by Tennet, the dutch TSO.

6.2.1 Simulation Results Westermeerwind

Execution of the rules published by RVO resulted in an average value of every MWh of imbalance of around 3.60 EUR MWh^{-1} for the years 2017 and 2018. An example calculation is included in Appendix E. The year 2016 is left out of this this Imbalance Model since the forecast timeseries for 2016 is incomplete.

In Figure 37 the results of the Imbalance Model imposed on 2017 data is shown. Due to the quadratic term in the objective function we see that large volumes of imbalance are penalized harder. Consistent with the sensitivity analysis presented in section 5.4.2, the BESS is able to reduce the exerted MAE partially without the need for a large(r) storage system. The determined BESS size is the same for both years as found in the results section 6.1.

Note: The illustrated results are using the same input as presented for the Battery Model (144 MWp wind farm and 50 MWp solar PV farm).

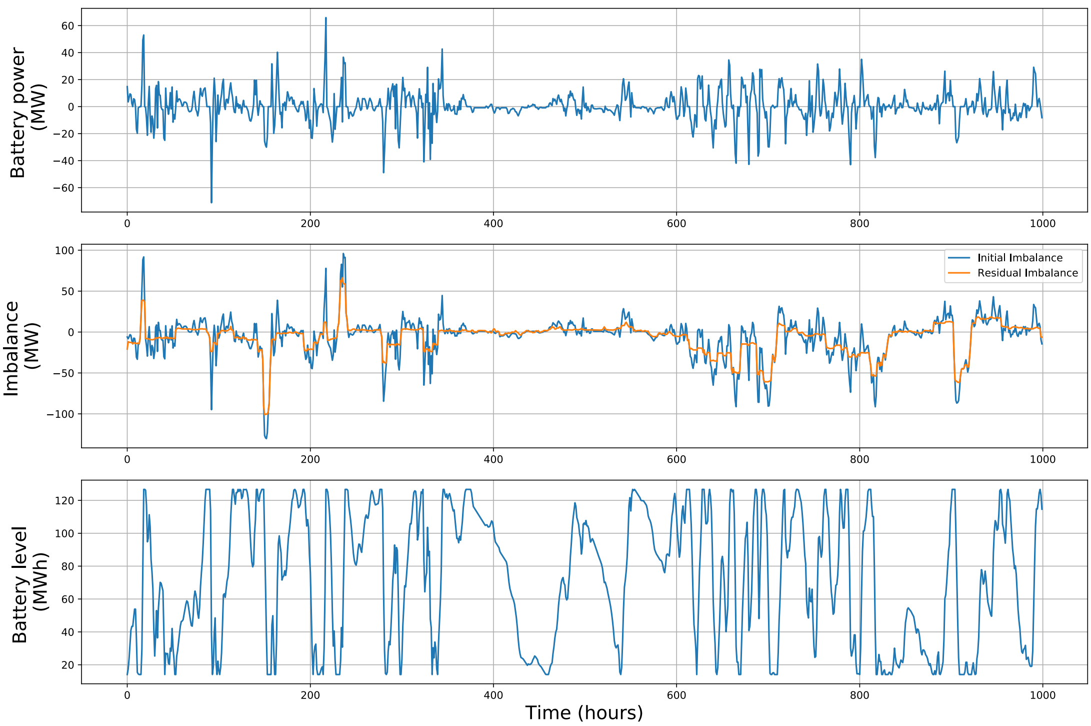


Figure 37: Results Imbalance Model 2017 (1000 consecutive hours): alpha = 3.6 EUR/MWh^2, $K_{battery}$ = 86 MWh & $P_{battery}max$ = 72 MW, Profit = 6.5 m EUR, and MAE = 7.1%

Figure 38 portrays the Imbalance Model applied to 2018. Clear from both figures (37 and 38) is that the residual imbalance is smooth and the Imbalance Model is forcing the sustainable power station in being more reliable (sub-objective 4, section 1.8).

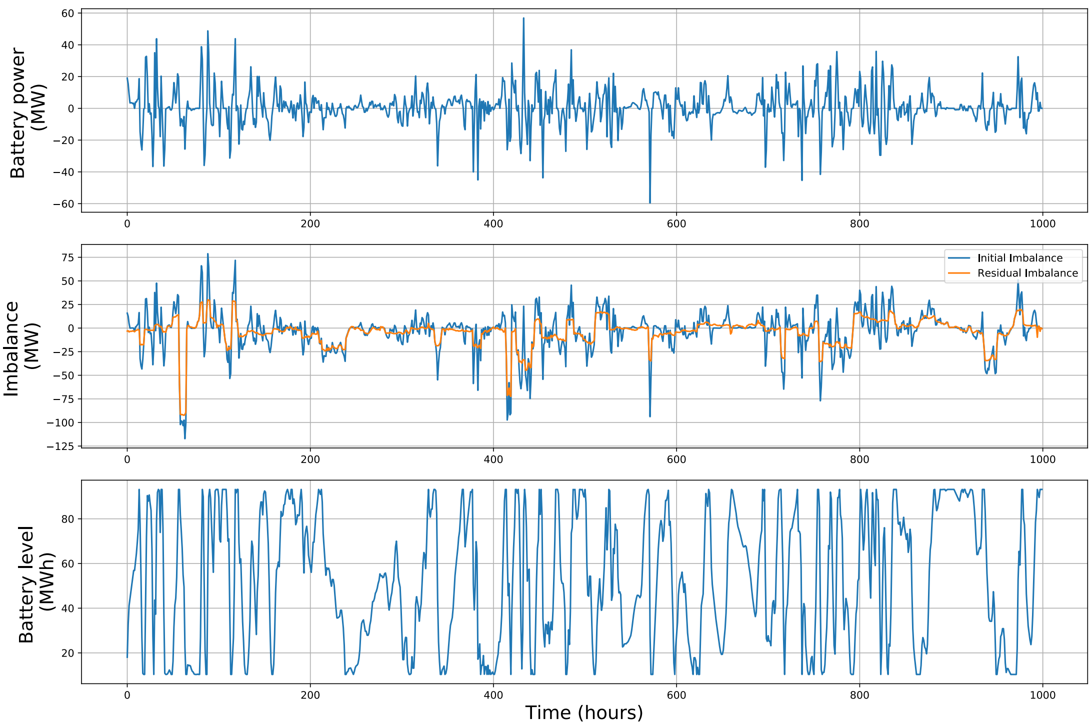


Figure 38: Results Imbalance Model 2018 (1000 consecutive hours): alpha = 3.6 EUR/MWh^2, $K_{battery}$ = 104 MWh & $P_{battery}$max = 87 MW, Profit = 7.6 m EUR, and MAE = 6.4%

		2017	**2018**
Alpha (α)	[EUR/MWh^2]	0.0	0.0
K_{solar}	[MWp]	50	50
$K_{battery}$	[MWh]	86	104
$P_{battery}max$	[MW]	72	57
Profit	[m EUR]	6.8	8.2
MAE pre	[% to nom. capacity]	9.8	9.5
MAE post	[% to nom. capacity]	15.0	16.6
Alpha (α)	[EUR/MWh^2]	3.6	3.6
K_{solar}	[MWp]	50	50
$K_{battery}$	[MWh]	86	104
$P_{battery}max$	[MW]	72	87
Profit	[m EUR]	6.5	7.6
MAE pre	[% to nom. capacity]	9.8	9.5
MAE post	[% to nom. capacity]	7.1	6.4
Alpha (α)	[EUR/MWh^2]	7.2	7.2
K_{solar}	[MWp]	50	50
$K_{battery}$	[MWh]	141	145
$P_{battery}max$	[MW]	79	59
Profit	[m EUR]	5.3	6.7
MAE pre	[% to nom. capacity]	9.8	9.5
MAE post	[% to nom. capacity]	6.3	5.8

Table 12: Dynamic simulation results Imbalance Model

The results presented in Table 12 show that using the battery partially for imbalance reduction is making the sustainable power station less economically feasible. The initial MAE is 9.8% in 2017 and 9.5% in 2018 without applying arbitrage. With an alpha of 3.60, the reduction in MAE is 28% for 2017 and 33% for 2018. The decrease in profit however is from 6.8 to 6.5 million Euro in 2017, which is a reduction of 5%. The profit for 2018 decreases from 8.2 to 7.6 million Euro (7% decrease).
The results presented without an imbalance penalty (α = 0.0) show a higher profit. Clearly, arbitrage on the APX market is more cost-effective. Decreasing imbalance is presumably more valuable with a deeper level of renewable energy penetration and when coal and gas fired plants are shut down. Currently, mainly coal and gas fired plants operate at the imbalance market. With the low fuel costs and economies of scale they outperform battery storage. Currently, the penalty a wind farm owner receives is too small to create here an incentive to be balance responsible.

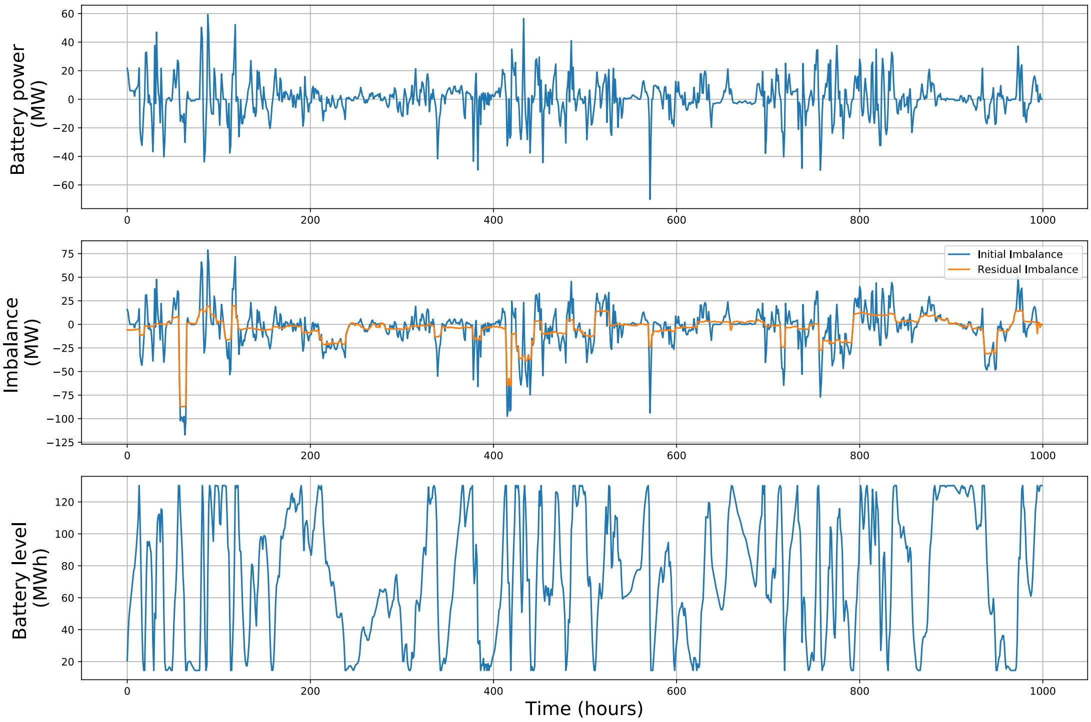


Figure 39: Results Imbalance Model 2018 (1000 consecutive hours): alpha = 7.2 EUR/MWh^2, $K_{battery}$ = 145 MWh & $P_{battery}$max = 59 MW, Profit = 6.7 m EUR, and MAE = 5.8%

At last, Figure 39 shows the modeled output for 2018 when the algorithm is excessively punishing imbalance in a possible 'future' scenario. It is assumed that the imbalance prices are more volatile with higher price differences and therefore the used value of alpha is 7.2 EUR/MWh^2 which is two times the value which it is now. Clearly, the residual imbalance here is much lower. However, the battery size needed for 2018 is also 40% larger (104 vs. 145 MWh) which results in a decrease in profit of 18% (from 8.2 to 6.7 million EURO) with respect to no imbalance penalty.

6.3 Battery PV Model

Application of the Battery PV model on the situation of Westermeerwind wind farm and corresponding grid-connection is presented here. The Battery PV Model is able to determine the optimal solar PV farm size and BESS size in a single run. It is found in the previous Battery Model, that forcing the system to store all the excess energy (zero curtailment constraint) may result in a relatively large battery size ($K_{battery}$). In this section the Battery PV Model is used to explore the configuration of a potential sustainable power station where the zero curtailment constraint has been released. Consequently, the presented optimization algorithm computes the trade-off between storing excess energy in the battery system and curtailing due to limiting grid connection capacity.

6.3.1 Simulation Results Westermeerwind

For this particular situation it is assumed that wind energy is prioritised first. And therefore, solar energy is curtailed when the electrical infrastructure is limiting. Inevitably, this is subject to the preference of the RES owner. For example when the subsidy scheme has come to its end (after 15 years) it is more cost-effective to tweak the one which is not subsidized anymore. The subsidy (SDE price) for Westermeerwind is 151 EUR MWh^{1}. As shown in section 6.1.1 the prospect of solar PV subsidy in 2020 is around 75 EUR MWh^{-1}. On this basis, curtailing solar PV power is assumed.

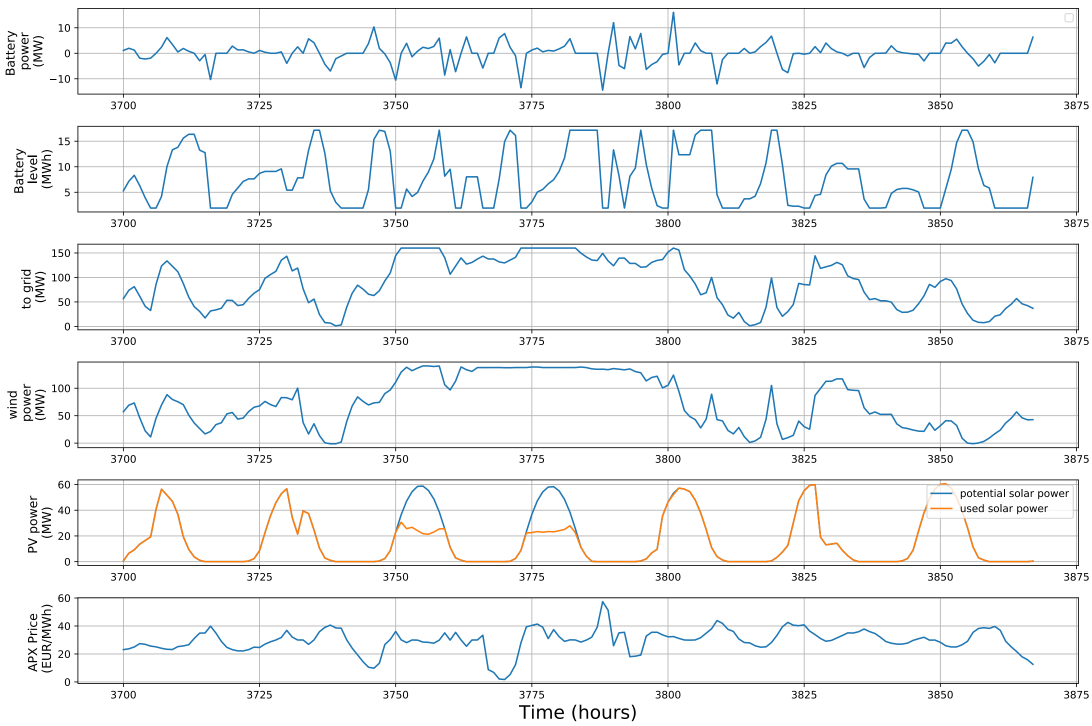


Figure 40: Dynamic simulation results Battery PV Model for 2017 (1 week): $K_{battery}$ = 19 MWh & $P_{battery}$max = 16 MW, and K_{solar} = 81 MWp.

Figure 40 shows the simulation results for the Battery PV Model on wind generation data and corresponding APX price for 2017. In accordance with the results presented of the Battery Model it is more beneficial to curtail a limited amount of solar power during peak production of the wind farm instead of over-sizing the BESS. When wind production and solar PV is maximum not all the power generated can be transported directly to the grid which can be seen in the fifth subplot. At hour 3750, the combined generation is almost above the cable capacity.
The BESS is completely discharged when the APX price is high and can be charged until full.

Optimization results Battery PV Model: 1000 consecutive hours in 2017

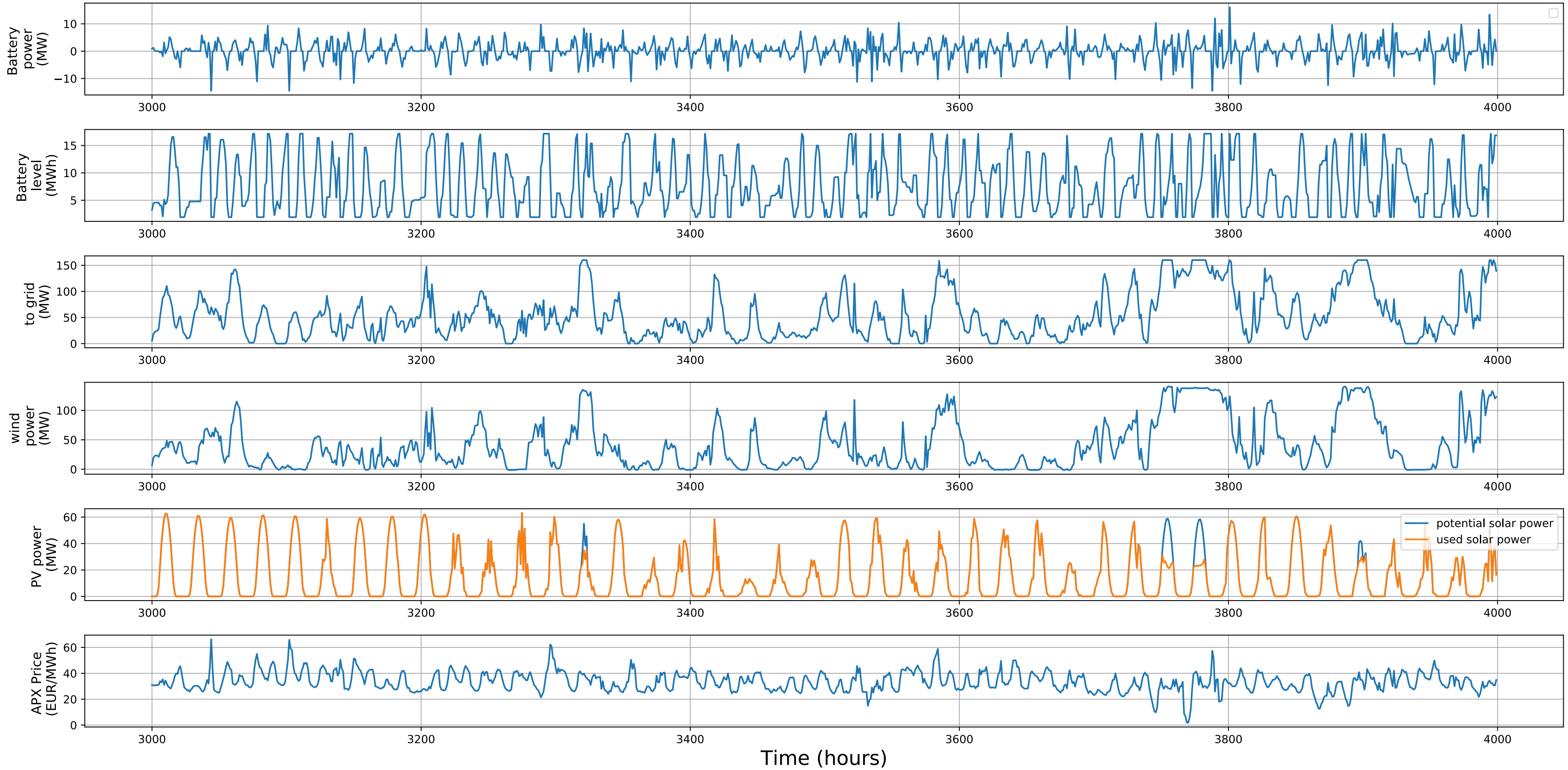


Figure 41: Dynamic simulation results Battery PV Model for 2017: Battery Power, Battery level, Power to grid, Real Wind power, and Solar power. $K_{battery}$ = 19 MWh & $P_{battery}$max = 16 MW, and K_{solar} = 81 MWp.

Figure 41 visualizes 1000 hours of generation of the modelled sustainable power station in 2017. The simulation results comprise the potential solar output and the used solar output. The used input parameters are; $C_{battery}$=450k MWh^{-1}, C_{solar}=520k MWp^{-1}, and C_{wind}=900k MWp^{-1}. It can be noted that it is sometimes preferred to curtail (not generate) a certain percentage of the solar power then over-sizing the system components.

Table 13 shows the results of the Battery PV Model imposed on the generation data of Westermeerwind for 2016, 2017, and 2018.

Note: In the results presented in Figure 41 and Table 13, it is estimated that the Capex is amortised linearly without salvage value. The solar PV farm and wind farm are depreciated in 15 years while the BESS is depreciated in 10 years.

		2016 full year	**2017 full year**	**2018 full year**
K_{solar}	[MWp]	56	81	230
Curtailed solar AEP	[%]	0.4	3.9	15
$K_{battery}$	[MWh]	16	19	11
$P_{battery}max$	[MW]	14	16	10
Revenue	[m EUR]	15	22	35
Profit	[m EUR]	12	19	26
Wind AEP	[GWh]	394	506	463
Average Weighted APX price	[EUR]	35	38	50

Table 13: Dynamic simulation results Battery PV Model

Table 13 shows interesting results whereas the size of the solar PV farm changes greatly. It is decided that the results for the Battery PV Model are a good first order approximation but significantly more years of data needs to be studied before the effect of wind and solar availability is minimized. The AEP of both wind and solar as well as the time of generation are influencing the optimal outcome and accuracy of the found answers. Moreover, the APX price during generation is very important for the configuration found. However, these findings indicate that the optimal solar PV farm is larger than calculated in the Battery Model in section 6.1, which is in line with the proposed hypothesis.

Curtailen vs. Significant Overplanting

Figure 42 reflects a completely different configuration. Remarkable in the results presented for 2018 is that a significant amount of the potential solar AEP needs to be curtailed. Analyzes of the various financial models of Ventolines has shown that for solar PV farms in the range 10-100 MWp, a significant amount of potential solar energy can be curtailed without a substantial decrease in the Internal Rate of Return (IRR) (Equity part). This lower production is possible due to the lower installation cost. The presented optimization problem calculates hereby the trade-off between curtailing and installing a smaller solar PV farm.

Optimization results Battery PV Model: 1000 consecutive hours in 2018

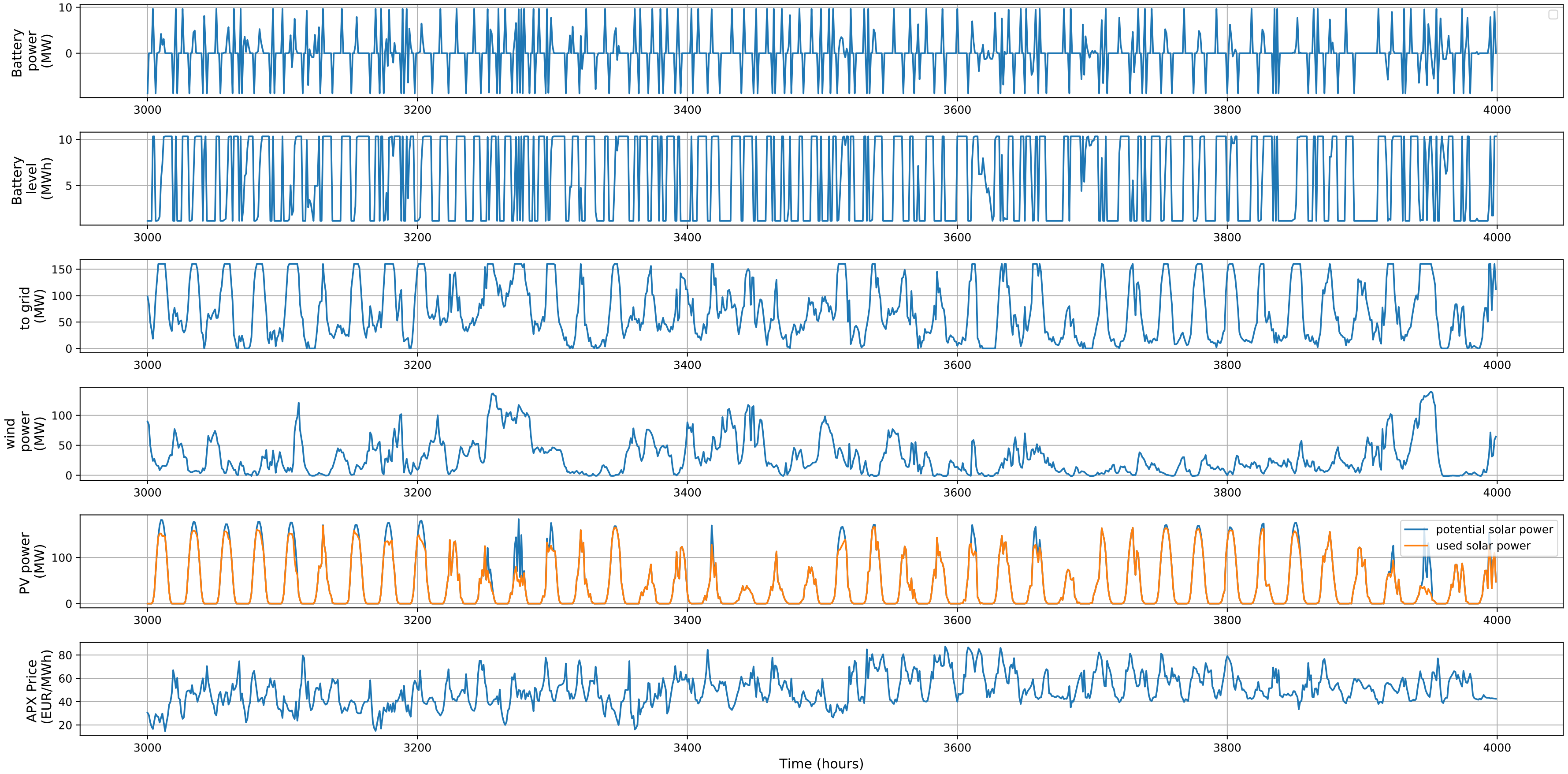


Figure 42: Dynamic simulation results Battery PV Model for 2018: Battery Power, Battery level, Power to grid, Real Wind power, and Solar power. $K_{battery} = 11$ MWh & $P_{battery}max = 10$ MW, and $K_{solar} = 230$ MWp.

6.4 Summary and Conclusion

Battery Model

From the simulation set-up and results presented in section 6.1, it can be concluded that being self-reliant, using all the potential renewable energy, and shifting the generation profile by peak shaving and arbitrage on the APX market result in a positive outcome of the objective function (maximizing profit). With the addition of different solar PV farm sizes and corresponding battery size, a new optimal configuration is computed (increased income) based on the data for 2016, 2017, and 2018. The computed battery size for the addition of small solar PV farms is only used for self-consumption and arbitrage. It is found that when the combined generation during peak availability is higher than the grid connection, the computed battery size increases rapidly, since curtailing energy is prohibited. The significant cost of installation for the BESS results in decreasing rates of return. Storing excess energy, applying arbitrage on the APX market, and being self-sufficient is insufficient for the additional investment. Nonetheless, cable pooling in combination with charging the BESS solely from own generation avoids peak-consumption prices and has a positive impact on the grid-connected storage business case in general. Based on the wind production of 2016, 2017, and 2018, the proposed optimal configuration for a sustainable power station at the location of Westermeerwind is with the addition of a ±30 MWp solar PV farm and a BESS of ±10 MWh.

Imbalance Model

The true value of every MWh of imbalance exerted by Westermeerwind is computed and is around 3.6 EUR MWh^{-1} for the years 2017 and 2018. Simulations of the Imbalance Model imposed on Westermeerwind show that penalizing imbalance with a value of 3.6 EUR/MWh^2 only makes the sustainable power station slightly more reliable. In addition, the decrease in MAE is around ±30% (28% for 2017 and 33% for 2018) while the decrease in profit is ±6% (in 2017 from 6.8 to 6.5 mEuro and in 2018 from 8.2 to 7.6 mEuro). The penalty used (3.6 EUR/MWh^2) is already higher than the actual value of imbalance (3.6 EUR MWh^{-1}). The Imbalance model uses the battery power minus the imbalance power squared. Initially the model was using the absolute value instead of quadratic. The solver (IPOPT) needed up to 15000 iterations and still reported sometimes the max iterations error. Moreover, running the algorithm for half year periods with the absolute value resulted in very long computation times and hereby reporting now and then the status that is was not able to find an optimal solution. Because of this reason imbalance is penalized quadraticly. A second observation is that the imbalance penalty needs to be relatively high to force the Imbalance Model in absorbing even more imbalance. By applying a higher penalty (α) the optimal battery size is rapidly increasing, as is the total cost of the system. A third remarkable observation is that with current imbalance prices the algorithm is able to decrease the difference between the 24-hour ahead forecast and measured generation without the need for a larger battery storage system. The battery capacity needed is identical to the scenario without an imbalance penalty. The battery capacity needed is again determined by the largest volume of simultaneity in peak production (see Figure 35). Further in Table 12 can be seen that in a possible 'future' scenario when the value of imbalance is larger rapidly a larger capacity (MWh) is needed.

A last observation is that the residual imbalance after penalizing is much more fluent, the peaks and troughs are decreased due to the quadratic approach. The potential value of these large quantities of imbalance might be higher than the value calculated in Appendix E since large imbalance is harder to balance for market parties. However, with current imbalance prices and battery capex it is not feasible to make a business case for battery storage only based on imbalance management. For Westermeerwind, the cost of imbalance is currently smaller than the earnings that can be achieved with arbitrage on the APX market. The method used can be seen as a conservative first order approximation.

Battery PV Model

Simulation results of the Battery PV Model revealed that it is far from cost optimal to size the BESS and solar PV farm with the zero curtailment constraint. Findings from multiple studies and the results presented of the Battery PV model imposed on the situation of Westermeerwind wind farm show that curtailment of renewable energy is currently cheaper than investment in a grid-connected BESS.
Curtailing of 'cheap' solar and wind power is therefore currently seen in the market. Looking for the optimal configuration of Westermeerwind while solar curtailment (due to limiting cable capacity) is accepted results in a different outcome than presented in section 6.1. Simulation results for 2016, 2017, and 2018 of the Battery PV model indicate that significant overplanting on the existing infrastructure is most profitable. Simulations of multiple years of wind and solar PV generation data is needed to improve accuracy and minimize the effect of availability and intermittency. Based on the limited solar and wind simulations, a different configuration is quantified with a larger solar PV farm and a 11 - 19 MWh BESS. The calculated solar PV farm size is 56 MWp for 2016, 81 MWp for 2017, and 230 MWp for 2018.

Within these configurations a certain part of the potential solar power needs to be curtailed due to the electrical infrastructure limitations. For 2016 0.4%, for 2017 3.9%, and for 2018 15% of the solar AEP needs to be curtailed. The 15% calculated seems very high but one should consider that by cable pooling the installation cost is decreased by sharing a grid connection and transformer. Moreover, analyses of Ventolines' Financial models of solar PV projects in the range from 10-100 MWp revealed that 10-13% of the AEP may be curtailed with the same internal rate of return. However, more solar and wind input data is needed to minimize this effect of solar and wind availability on the computed configuration and to come to an optimal configuration for a period of multiple years.

Energy Storage For Peak Availability

The calculation methods use a year of generation data which gives a valuable indication and the models proposed can be applied to other onshore wind locations. The cost-benefit analysis furthermore shows that battery storage in the Netherlands is unlikely capable of storing all energy during peak production. It must be noted however that the battery storage business case is highly dependant on the difference in peak and off-peak price and installation costs which is subject to a wide range of factors. Sizing based on self-consumption and arbitrage is found correct as a starting point, whereas development in phases (adding more MWh later) is possible with more price volatility on the APX and imbalance market.

7 Conclusions and Recommendations

By developing a methodology for the optimal design of wind power, solar PV power, and storage at a single (limiting) grid connection, this research has come to its conclusion section. Along with the findings presented in chapter five and six this final chapter aims to summarize the overall conclusions related to the different objectives. At last, recommendations will be given on how the sustainable power station can be designed even more efficiently and what the limitations of this research are.

7.1 Power System Integration

The current need for electricity is predominantly covered by coal-fired, gas-fired, hydro and nuclear power plants. Although these are reliable, safe, and easy to control, society is shifting towards a power system composed of RES. These relatively new sources do not directly contribute in the emission of greenhouse gases (mainly CO_2) and are infinite. When integrating significant amounts of solar PV and wind power in the European power system, technical challenges originate due to the sparsity of available grid connections and the uncontrollable behavior of both wind and solar PV. Demand is largely unresponsive to price and thus supply must follow demand. The general question hereby is how can we design a cost optimal system which is able to take over the current coal and gas fired plants while maintaining a reliable and safe supply of electricity. Exploring how the configuration would be when all potential renewable power is generated instead of curtailing a certain amount. And also, if battery energy storage in combination with wind energy is capable of following the 24-hour ahead forecasted production (making it hereby a 100% reliable power plant).

Scientific Significance
As explained in the literature review section this study is fundamentally different from previous studies and is focussing on grid connected storage in a future western electricity system. Where the renewable energy penetration level is currently low but is increasing rapidly. Grid-connected energy storage and cable pooling (Solar PV & Wind) is often suggested as a logical complement for a power system which is changing to a system powered by RES. While cable pooling and battery energy storage appears to be a sensible link in the transition phase, the knowledge is sparse. Safe and prolonged operation of battery energy storage systems is required where special attention is applied to DOD, round-trip efficiency, cycling life, and installation cost.
How short to medium-term storage can be used in the Dutch power system is therefore studied. Storage business cases are highly dependent on the spread between peak and off-peak prices. These are by definition much smaller for interconnected systems compared to island systems. Subsequently, existing studies never use western electricity prices or look into the value of minimizing imbalance. Finally, the grid connection capacity limitations are always excluded.

This research lays its focus on developing a methodology for the optimal design of wind power, solar PV power, and storage at a single (limiting) grid connection. The method proposed is considered to be optimal for the current and future western European electricity system. Optimization of the sustainable power station is done on a short to medium-term. The developed methodology takes both economical, social, environmental, and electricity market aspects into account. The constraints of battery storage and assumptions used are translated into a set of linear equations. These linear equations and an objective function have resulted in an optimization algorithm. The algorithm uses the real-time APX price as the value for every MWh of energy produced without subsidy as this will be the case in the future power system. The overall objective is to find the battery capacity [MWh] in the Battery Model and Imbalance Model. In the Battery PV model, the algorithm also finds the optimal solar PV farm size [MWp]. This research project considers the grid-congestion difficulties as an important driver for combining wind, solar and grid-connected storage optimal on a single grid connection. Therefore it is deliberately different than existing studies focussing on small 'off-grid' island systems.

This research includes three different models and the literature required to justify the proposed models step-by-step. The steps are summed up below:

1. Correctly simulate the wind and solar PV power output over time when real time generation output is absent (Chapter 2).
2. In depth analysis about simultaneity of solar and wind power production on a limiting electrical infrastructure in the Netherlands (Chapter 3).
3. Development of a Battery Model (optimization algorithm) that determines how much storage capacity is needed for a given configuration to be self-supporting, (i.e. the self-consumption comes from the BESS), where the storage system is charged by own generation, and where zero energy is curtailed (Chapter 4 & 5).
4. Development of an Imbalance Model (optimization algorithm) that ensures a more reliable generation profile. The battery will discharge at periods that the generation is lower than forecasted (pos. imbalance), and will charge in times that the generation is higher than forecasted (neg. imbalance). Again this model has to be self-sufficient, charged by own generation, and zero energy is curtailed (Chapter 4 & 5).
5. To write a Battery PV Model (optimization algorithm) that is able to determine the most cost optimal solar PV farm size and battery size for an existing wind farm with surplus cable capacity (Chapter 4 & 5).
6. Application of all the models proposed on a representative wind farm in the Netherlands (Chapter 6).

Case study Westermeerwind
The Battery Model imposed on the situation of Westermeerwind indicated that based on generation data for 2016, 2017, and 2018 a new optimal configuration is computed. The computed configuration is with the addition of a solar PV farm of ±30 MWp and a BESS of ±10 MWh. With this proposed configuration the sustainable power station is self-reliant, uses all the potential renewable energy, and applies arbitrage on the APX market. The computed configuration results in a positive outcome of the objective function (maximizing profit) where an increased income has been achieved. As an input parameter for the Imbalance Model the true value of every MWh of imbalance exerted by Westermeerwind is computed and estimated at around 3.6 EUR MWh^{-1} for the years 2017 and 2018. Simulations of the Imbalance Model imposed on Westermeerwind show that penalizing imbalance with a value of 3.6 EUR/MWh^2 only makes the sustainable power station slightly more reliable. Here, Imbalance is penalized quadratic which gives a fair first order approximation. In addition, the decrease in MAE is 28% for 2017 and 33% for 2018 while the decrease in profit is ±6% (in 2017 from 6.8 to 6.5 million Euro and in 2018 from 8.2 to 7.6 million Euro). At last, simulation results of the Battery PV Model revealed that it is far from cost optimal to size the BESS and solar PV farm with the zero curtailment constraint. Regardless from the 'limited' solar and wind simulations, a different configuration is quantified. The calculated optimal solar PV farm and storage size is 56 MWp with a 16 MWh BESS for 2016, 81 MWp with a 19 MWh BESS for 2017, and 230 MWp with a 11 MWh BESS for 2018. The amount of solar AEP that needs to be curtailed for the given configurations is for 2016 0.4%, for 2017 3.9%, and for 2018 15%.

Optimal Design Sustainable Power Station
From the results presented in the case study and simultaneity analysis some observations can be made. The first has to do with occurrence of peak production of both wind and solar power. Long term simulations up to 10 years reveal that simultaneity in peak production is limited and seldom leads to a combined generation above the cable capacity. The complementarity of solar PV and wind is best on a seasonal scale. The daily average production is for both wind and solar around noon. Using the existing electrical infrastructure more optimal is however very important in periods where available grid connections for new RES projects are extremely sparse. The second observation is that when peak production occurs, this is happening hour after hour mostly. Hence, storing all excess energy can only be done using a large BESS, which would then be used only a couple of times a year. A third observation is that a small storage

system is adequate in making the sustainable power station self-sufficient whilst maintaining a healthy business case. A fourth observation is that the BESS is capable of reducing self-exerted imbalance. An accurate first order approximation is presented. With regard to the MAE, large scale storage is needed to decrease this to a minimum. Currently, the penalty is too low to create a feasible incentive to become a balance responsible party. A fifth observation is that when curtailment is allowed a different configuration is obtained. Here, the outcome of the objective function results in a configuration with significant overplanting whilst a share of the potential solar PV power is curtailed.

Large Scale Storage Integration
From this research, however, it can be concluded that BESS for storing excess energy, self-consumption, reducing imbalance, and arbitrage is not the most efficient solution for the Netherlands. Nonetheless, it lays the foundation for an interconnected system model , not a technically already severely constrained system to begin with, such as an island system. The model is built-up with the current market circumstances and is in line with what can be seen in the market. The set-up is right and incorporates a fundamentally different analysis of the outlined problem. A cost-benefit analysis of the Westermeerwind wind farm provide some interesting results and can be used as a fair indication for a wide range of onshore wind farms where (large) quantities of solar power can be installed without the need for amplifying the high-voltage grid. The presented results vary a lot and are heavily dependant on the timing of generation, corresponding electricity price, and whether or not curtailment is allowed. The different models presented make use of electricity prices of the past which are no guarantee for future years. By splitting this sizing study in different optimization problems, each battery service and value is examined individually. Each battery service examined does have value which can be stacked. Although the control strategy does not seems the most cost effective, it is capable of producing a more stable and reliable generation profile. It can be concluded that the results from the Battery Model can act as a starting point. A new investment decision may be made after a couple of years of generation which could lead to a configuration more in line with the results from the Battery PV Model. Both solar PV and BESS are modular solutions and can be broadened when more data is available and the model is validated.

It can furthermore be noted that combining battery storage and solar PV to an existing wind farm leads to a value increase of the generated power.

The optimization algorithm is built in Python 3.0, an open source programming language. Python has the advantage of having numerous publicly available libraries including the optimization library PYOMO. The objective used is simple and tries to maximize the profit.

7.2 Recommendations

The Netherlands is fully engaged in the transition to a renewable powered electricity system. Strong interconnections and storage systems are extremely important due to the intermittent behavior of both solar PV and wind energy. System integration plays a vast role in this transition phase. Hybrid systems should not only be investigated for 'isolated' island or small systems.

In this research, some important steps have been taken towards the design of a grid-connected optimal system. An important simulation result is that the results presented are consistent with what can be seen in the market. Large-scale grid connected battery storage is not yet ready for system integration. The proposed models should be extended further to include acting directly on the FCR- and imbalance market. Due to the uncertainties regarding bidding and acceptation on the FCR market, this has been left out of the proposed models. However, most battery systems are currently financed on this source of income. With the recent change of 1 week tenders to daily tenders this market has become more accessible.

Furthermore, the model needs to be extended by the possibility to determine what the 'cost' optimal configuration would be without the already installed wind farm. The effect of choosing offshore wind power output and or floating solar can be studied in the proposed model. Similarly, the model proposed needs to be studied with different storage systems.

Execution of these recommendations could be an important step toward the implementation of hybrid systems in the future power system.

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Appendices

A Renewable Energy Sources

True Cost of Renewables provided by the IRENA 2016.

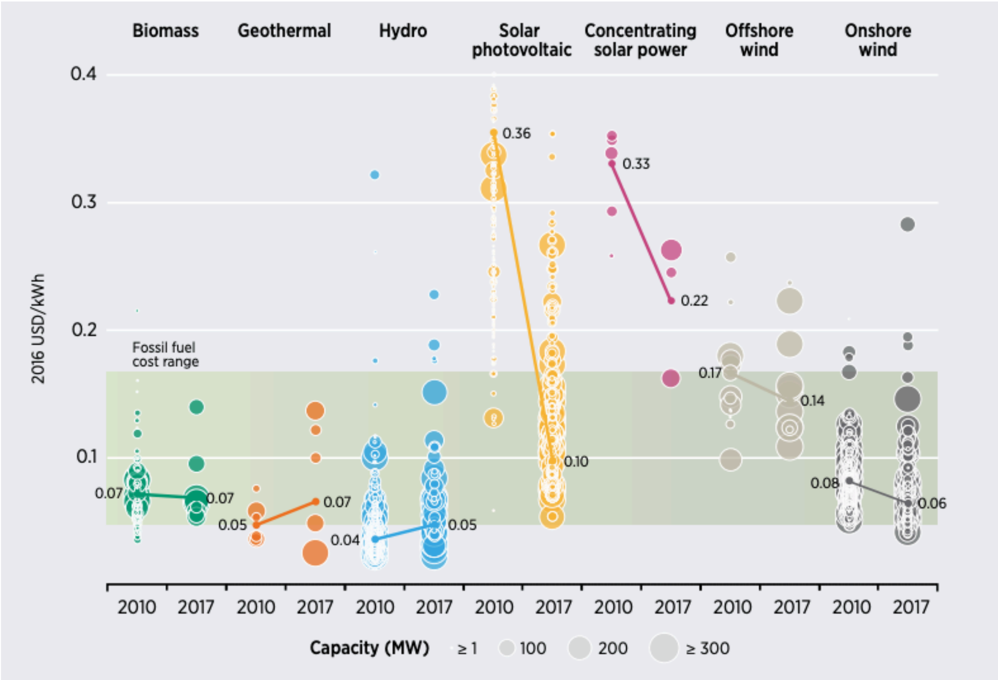

Figure 43: Renewables competitiveness continues to improve, 2016[6]

B Wind Validation

Validation of the Simulated Wind Power Production

Via the wind farm owner and Ventolines the time series for the 144 MW wind farm came available. In this data series the measured power, self-consumption for very low wind speeds and the measured power output is visible. In Figure 45 the difference between the measured and simulated power output per hour is shown for 7 consecutive days in October. The negative power output shows that during periods of low wind availability energy is needed instead of being produced. The high peaks of internal energy consumption come from periods in which the turbine is yawing. Analysation of the AEP is shown in Table 4. Also a typical 20MW wind farm generation data is analyzed and the 10m wind speed data set is used in the model to validate the AEP.

Note that in the measured power output also periods of maintenance and periods in which curtailment took place (due to negative prices on the power markets) are listed.

Output	Value
Total Annual Energy production (simulated)	412 GWh
Total Annual Energy production (measured)	422 GWh
Self consumption (simulated)	-1.1 GWh
Self consumption (measured)	-0.7 GWh

Table 14: Energy content of the model versus real generation data

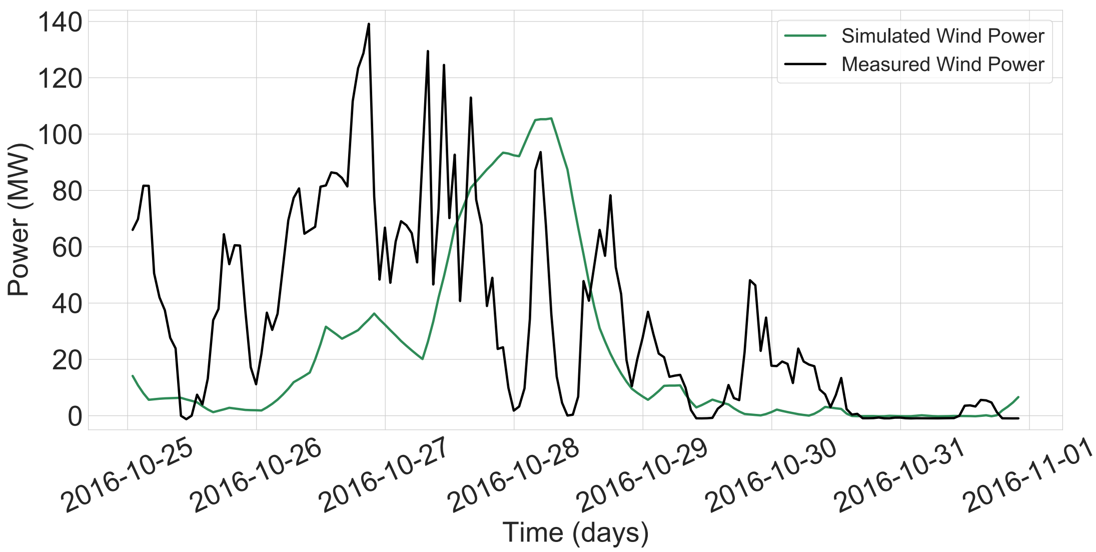

Figure 44: Real generation data and simulated wind power output, October 2016, Westermeerwind windfarm, 144MWp installed capacity.

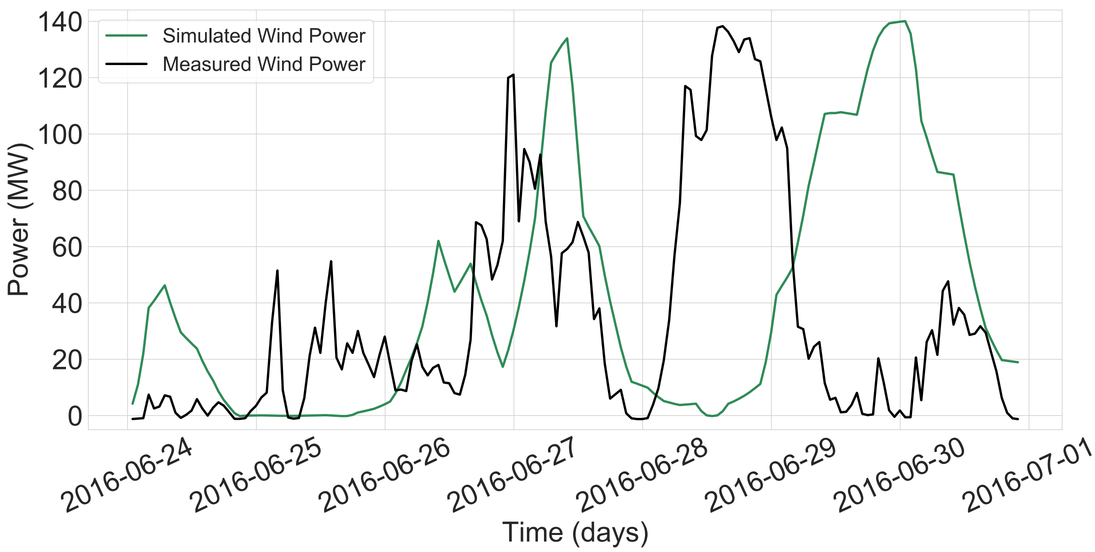

Figure 45: Real generation data and simulated wind power output, October 2016, Westermeerwind windfarm, 144MWp installed capacity.

C Visualisation Energy Flows

Energy Flow in Battery Energy Storage System

The conceptual model provides insight in the energy flowing in (charging) and flowing out (discharging) of the BESS. This section gives an example of the battery flows in the battery in accordance with the flowchart presented in Figure 22. The power in and out has been calculated by implementing a different efficiency for charging (η_{charge}) and discharging ($\eta_{discharge}$). In the following figures four scenarios will be explained; (1) No limiting electrical infrastructure, (2) Limiting electrical infrastructure (e.g. P_{solar} plus P_{wind} is larger than P_{togrid}), and (3) discharging while the combination of solar and wind is lower than the cable capacity. (4) Arbitrage, the combination of wind and solar is lower than the cable capacity. The electricity generated is stored in stead of fed onto the grid directly. In the figures presented the energy stored in the battery is indicated by the battery level (E_B) for every t.

Scenario 1

Figure 46 exemplifies how the energy is flowing through the system when the total generation (Solar plus Wind) is lower than the cable capacity (P_{togrid}). The conceptual model decides in the control system that in this scenario the power is directly transported to the grid.

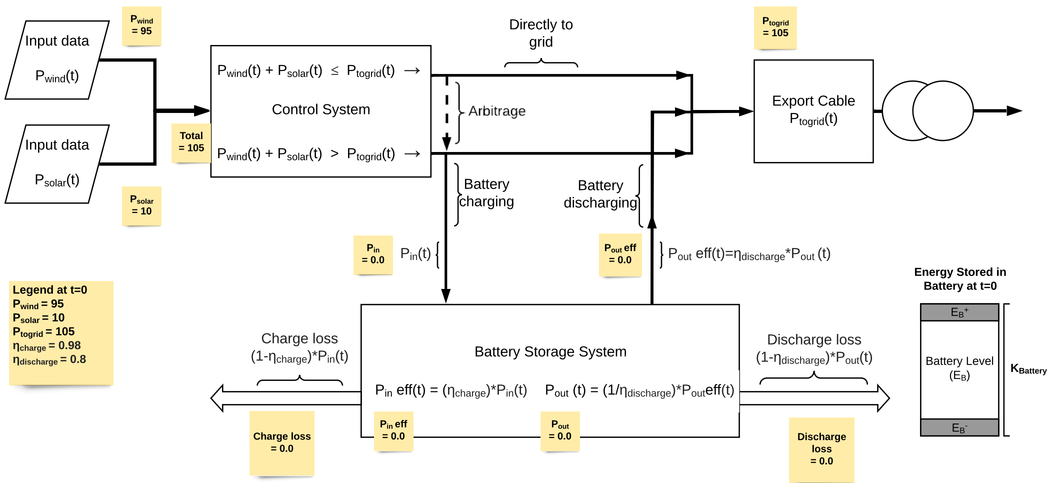

Figure 46: Energy flow Diagram BESS and control system box at t=0. All the generated power is directly transported to the grid. Discharge and charge losses are depicted by blank arrows.

Scenario 2

In Figure 47, an illustrative example is given for a consecutive hour after the situation in Figure 46. Here, the sum of both solar and wind production is higher than the cable capacity. Only the excess energy ($P_{solar} + P_{wind} > P_{togrid}$) is fed into the BESS. In this example the efficiencies are set at two different (random) values to indicate how the model works. Simultaneously there is 160 MW flowing directly to the grid via the export cable.

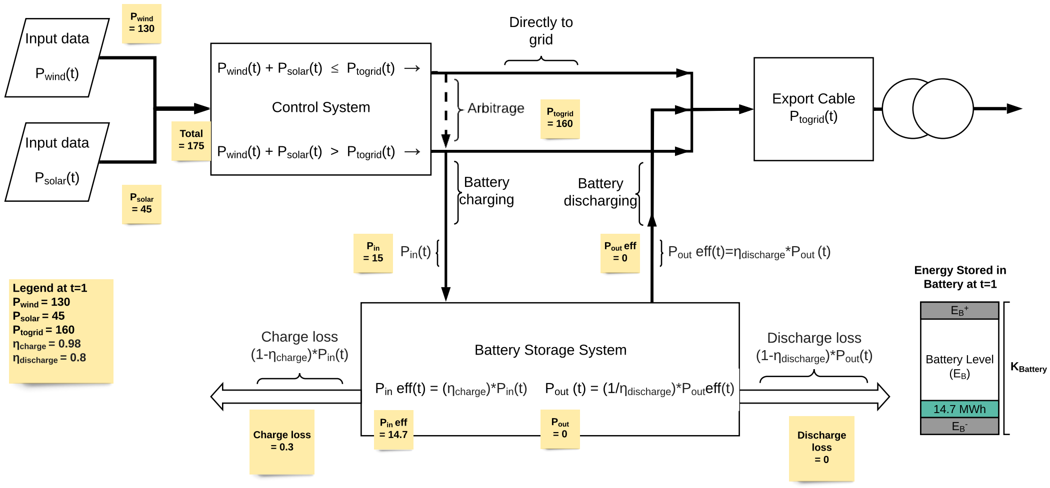

Figure 47: Energy flow Diagram BESS and control system box during **charging** at t=1. Discharge and charge losses are depicted by blank arrows.

Scenario 3

Figure 48 exemplifies how the conceptual model calculates how much can be discharged at maximum. The sum of P_{out}eff, P_{wind}, and P_{solar} is limited by the cable capacity (160 MVA). Consequently, P_{out} can be higher than the remaining cable capacity, and thus explains the $\frac{1}{\eta}$ term.

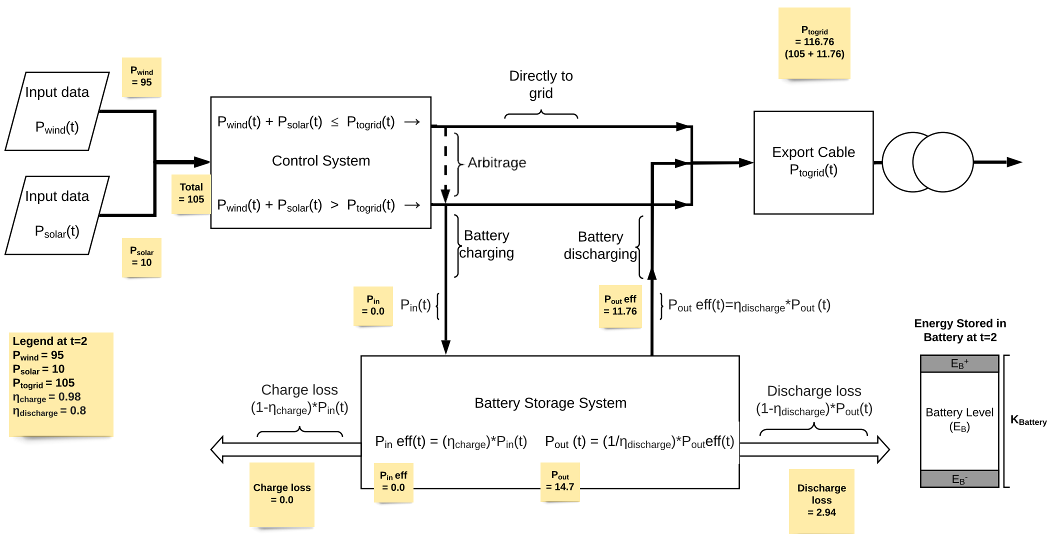

Figure 48: Energy flow Diagram BESS and control system box during **discharging** at t=2. Discharge and charge losses are depicted by blank arrows.

Scenario 4

Figure 49 visualizes the energy flow in the model during arbitrage. The model is able to store electricity when the electricity price is low and sell it (discharge) when the price is high(er).

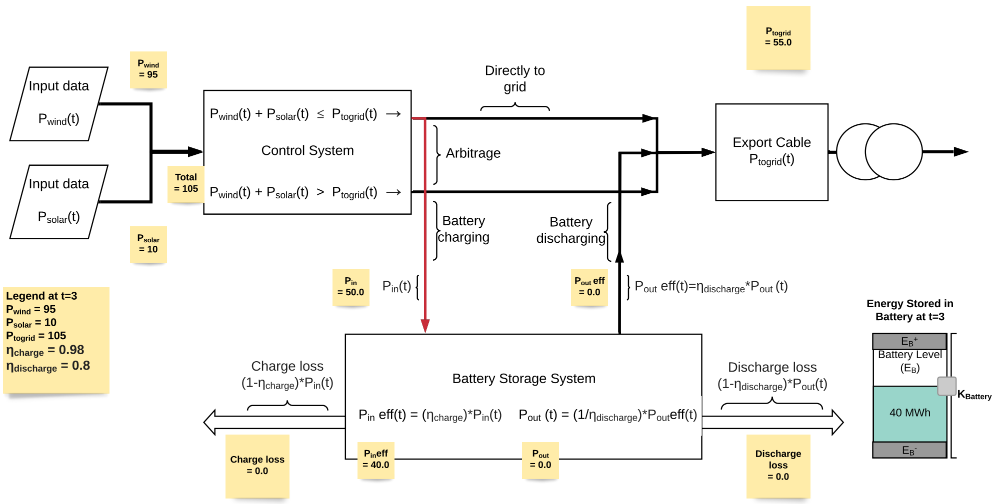

Figure 49: Energy flow Diagram BESS and control system box during **arbitrage** at t=3. Discharge and charge losses are depicted by blank arrows.

D Analytical Verification Battery Model

Integration by hand

Analytical verification battery size ($K_{battery}$). Area a (in Figure 23) is calculated by first integrating the solar function from t1 until t2. Similarly, the wind function is integrated over the same range. The sum of these two integrals is the integral over the consolidated function. The amount of energy which can be transported directly to the grid is equal to the integral over the cable capacity function (again from t1 until t2). The resulting part which cannot be transported needs to be stored in the BESS. Area a is therefore the integral over the consolidated function minus the integral over the cable capacity function and is .

$$\textbf{Charging:} \quad \eta_{in} * \int_{t_4}^{t_{19}} A\sin(\omega t) \quad dt \quad + \int_{t_4}^{t_{19}} W \quad dt \quad - \quad \int_{t_4}^{t_{19}} C \quad dt \tag{36}$$

$$\begin{aligned}
\textbf{Sine function (solar):} \int_{t_4}^{t_{19}} &= -\frac{24}{\pi} * \cos(\pi) - (-\frac{24}{\pi} * \cos(o)) \\
&= -\frac{24}{\pi} * \cos(\frac{19}{24}\pi) - (-\frac{24}{\pi} * \cos(\frac{4}{24} * \pi)) \\
&= (-7.64 * -(0.79)) - (-7.64 * \cos(0.52)) \\
&= (-7.64 * (-0.79)) + (7.64 * 0.87) \\
&= 12.68 * 50 \\
&= 634
\end{aligned}$$

$$\begin{aligned}
\textbf{Step function (wind):} \int_{t_4}^{t_{19}} &= 144 * (19 - 4) \\
&= 2160
\end{aligned}$$

$$\begin{aligned}
\textbf{Cable capacity:} \int_{t_4}^{t_{19}} &= 160 * (19 - 4) \\
&= 2400
\end{aligned}$$

$$\begin{aligned}
\textbf{Charging:} &= \eta_{in} * [634 + 2160 - 2400] \\
&= 0.98 * 394 \qquad\qquad (37a) \\
&= 386
\end{aligned}$$

The number quantified by the battery model is 388 MWh. The small difference (2MWh) is in the charge efficiency times the charging area for every t. By doing this in separate steps the outcome of the charging integral is 388 MWh (387.59).

E Example Calculation Imbalance

True Value Imbalance

The true value of every MWh imbalance can be computed and is wind farm specific. The calculation is here performed for the Westermeerwind wind farm. The calculation has been carried out under the assumption that this market party is acting as a price taker and not as a price maker. This means that the total volume produced is not sufficient to change the market prices. Consequently not able to change the profile. The method used is equal to the method described in a report provided by ECN (PBL, Voorlopige correctiebedragen 2018, SDE+ [59]) in which the common rules for determining profile and imbalance factor are described.

$$imbalance \quad value = pos.imbalance * \lambda^{+} + neg.imbalance * \lambda^{-} \tag{38}$$

Description	2018	2017
1. Total net production	463 GWh	503 GWh
2. Total weighted value excl. imbalance	24.50 Million Euro	19.13 Million Euro
4. Total weighted value incl. imbalance	21.79 Million Euro	17.3 Million Euro
5. Average unweighted APX price	52.52 Euro MWh^{-1}	39.33 Euro MWh^{-1}
6. Average weighted APX price	50.03 Euro MWh^{-1}	37.78 Euro MWh^{-1}
7. Profile factor	0.96	0.96
8. Imbalance factor	0.93	0.91
9. Profile Imbalance factor	0.90	0.87
10. True value imbalance	3.60 Euro MWh^{-1}	3.62 Euro MWh^{-1}

Table 15: Overview: Example calculation Profile and Imbalance factor for a case specific onshore wind farm for 2017 & 2018 full year.

Below a complete description of each number listed in Table 15:
1. Total net production is the total production minus total consumption.
Where production is production minus the electricity used for self-consumption (e.g. the production which is fed into the grid). Consumption is the power extracted from the grid when the farm is producing less than needed for self-consumption.
2. Total weighted value excluding imbalance Forecasted production times APX price.
3. Imbalance value Imbalance times imbalance price (long or short price, see equation 38).
4. Total weighted value including imbalance Total weight value excluding imbalance plus Imbalance value.
5. Average unweighted APX price Average APX price.
6. Average weighted APX price Volume weighted APX price.
7. Profile factor Average weighted APX price divided by the Average unweighted APX price.
8. Imbalance factor Total weighted value including imbalance divided by the Average weighted APX price.
9. Profile Imbalance factor Profile imbalance factor (PIF) Profile factor times Imbalance factor.
10. True value imbalance 1 minus the imbalance factor times the Average unweighted APX

price.

In summary, the sustainable power station itself is not able to change the profile and thus the true value of imbalance or additional gain that can be obtained is herefore only using the imbalance factor and neglecting the profile factor. Last years, the PIF was in a range between 0.82 and 0.90 for onshore wind. The profile and imbalance factor is based on public ENTSO-E data and data from market parties.

F Battery Model

Pyomo Code

```python
## Python 3.0
# Import Libraries

import sys
import pandas as pd
from pyomo.environ import *
from pyomo.opt import *
import matplotlib.pyplot as plt
import numpy as np
import matplotlib.ticker as mtick
import math

## Battery Model
# The Battery Model determines the optimal BESS size in MWh
# wind and solar power per hour are used as input
# Further, the corresponding electricity price is used as input


# Reading solar, wind, and APX data into dataframe
path_complete = 'WMW_1mw_zon_final_2018.xlsx'
completeData = pd.read_excel(path_complete)

# ---------------------------------------- #
# Input parameters
solar_farm_size = 50.0 #MWp
wind_farm_size = 144.0 #MWp
tau = 1.0 #hour (max c-rate)
EB_0 = 0.0 #start battery level
eta_in = 0.95 #charge efficiency
eta_out = 0.95 #discharge efficiency

# select range in the input data
tstart = 2000
tend = 2100
TT = tend - tstart
export_limit = 160.0

# Battery Capex per MWh
C_batt = 450000.0
Tlife_batt = 10.0 * 8760 #year * hours
C_annualized_batt = (C_batt*TT)/Tlife_batt

# Solar PV farm Capex per MW
C_solar = 520000.0
Tlife_solar = 15.0 * 8760 #year * hours
C_annualized_solar = (C_solar*TT)/Tlife_solar

# Wind farm Capex per MW
C_wind = 900000.0
Tlife_wind = 15.0 * 8760 #year * hours
C_annualized_wind = (C_wind*TT)/Tlife_wind
```

```
# penalty factor
rho1 = 5e2
rho2 = 1e-3

# ----------------------------------------- #
# converting different timeseries to lists
apx_price = np.array(completeData['apx_price'].tolist()[tstart:tend])
solar = np.array(completeData['solar_new'].tolist()[tstart:tend])*solar_farm_size
# wind = np.array(completeData['wind_power'].tolist()[tstart:tend])
wind = np.array(completeData['WMW_real'].tolist()[tstart:tend])


T = list(range(solar.shape[0]))
# computed optimal battery size in MWh
K = ['k_battery']

# print(completeData.head(5))

# Declare Concrete Model
model = ConcreteModel()
# model.t = Set(initialize=T, doc='Timesteps')
# model.I = RangeSet(1, 30)
# model.I = Set()

# loop over input parameters /indexeren
apx_price_dict = {t:apx_price[t] for t in T}
solar_dict = {t:solar[t] for t in T}
wind_dict = {t:wind[t] for t in T}


# ----------------------------------------- #
# Setting all input parameters
model.apx_price = Param(T, initialize=apx_price_dict, doc = 'APX Price (EUR/MWh)')
model.p_solar = Param(T, initialize=solar_dict, doc = 'Solar power (MW)')
model.p_wind = Param(T, initialize=wind_dict, doc = 'Wind power (MW)')


# ----------------------------------------- #
# Setting all variables
model.to_grid = Var(T, bounds=(0.0,export_limit), doc = 'Export power (MW)')
model.p_in = Var(T, bounds=(0.0,np.Infinity), doc = 'Charging power (MW)')
model.p_out = Var(T, bounds=(0.0,np.Infinity), doc = 'Discharging power (MW)')
model.EB = Var(T, bounds=(EB_0,np.Infinity), doc = 'Battery Level (MWh)')
model.ess = Var(K, bounds=(0.0,np.Infinity), doc = 'Storage size (MWh)')
model.curt = Var(T, bounds=(0.0,np.Infinity), doc = 'Curtailed Power(MW)')


# ----------------------------------------- #
# Setting up all constraints
# upper and lower battery level limit
# the battery level (EB) cannot be lower than 0.1, and above 0.9 times the battery
# capacity (k_battery) computed
def EB_upper(model,t):
    return model.EB[t] <= 0.9 * model.ess['k_battery']
model.upper_max = Constraint(T, rule=EB_upper, doc = 'E_batt upper limit')
```

```
def EB_lower(model,t):
    return model.EB[t] >= 0.1 * model.ess['k_battery']
model.lower_max = Constraint(T, rule=EB_lower, doc = 'E_batt lower limit')


# Maximum charging and discharging power limits
# the maximum charging and discharging power are the battery capacity found in MWh
# divided by tau in hours
def p_in_max(model,t):
    return model.p_in[t] <= (model.ess['k_battery']/tau)
model.p_in_max = Constraint(T, rule=p_in_max, doc = 'Maximum power in')

def p_out_max(model,t):
    return model.p_out[t] <= (model.ess['k_battery']/tau)
model.p_out_max = Constraint(T, rule=p_out_max, doc = 'Maximum power out')


# Battery level equation
# the battery level starts at soc_0
# at each index the previous energy in the battery is summed by the energy what
# needs to be stored during the charging scenario. During discharging the power
# out of the battery is substracted from the previous energy stored in the
# battery (battery level).
def Battery_level_rule(model,t):
    if(t == 0):
        return model.EB[t] == soc_0 + eta_in*model.p_in[t] - (1.0/eta_out)\
        *model.p_out[t]
    else:
        return model.EB[t] == model.EB[t-1] + eta_in*model.p_in[t]\
        -(1.0/eta_out)* model.p_out[t]
    model.state_equation = Constraint(T, rule=Battery_level_rule, \
                                      doc = 'Battery level equation')

# Balance of system equation
# the balance rule ensures that the system is never pulling electricity from
# the grid when wind power and solar power combined are above the power to the
# grid (cable capacity limit) this can flow in the battery system by power_in.
# When the combined generation is lower than the cable capacity the battery can
# discharge via power_out.
def balance_rule(model,t):
#      return -model.to_grid[t] - model.curt[t] + model.p_out[t] - model.p_in[t]
#      + model.p_wind[t] + model.p_solar[t] == 0
    return -model.to_grid[t] + model.p_out[t] - model.p_in[t] + model.p_wind[t]\
    + model.p_solar[t] == 0.0
model.balance_equation = Constraint(T, rule=balance_rule, doc='Load balance')

# Objective function
# maximize profit by selling electricity to the grid
# rho1 prevents the model from charging and discharging at the same time
def objective_rule(model):
    output = sum(model.apx_price[t]*model.to_grid[t] for t in T)\
    - (C_annualized_batt*model.ess['k_battery'] + C_annualized_solar*solar_farm_size)\
    - sum((rho1*model.p_out[t]*model.p_in[t] for t in T))
    return output
model.objective = Objective(rule = objective_rule, sense=maximize, \
```

```
                            doc='Objective function')

def pyomo_postprocess(options=None, instance=None, results=None):
    model.objective.display()


# ---------------------------------------- #
# Specifying the Solver
solver = SolverFactory('ipopt')
# changing the max. number of iterations of the solver
solver.options['max_iter']= 15000
# printing the solver results
solver.solve(model).write()
#--------------------------------------- #

p_in = [model.p_in.get_values()[t] for t in T]
p_in = np.asarray(p_in)
p_out = [model.p_out.get_values()[t] for t in T]
p_out = np.asarray(p_out)
to_grid = [model.to_grid.get_values()[t] for t in T]
to_grid = np.asarray(to_grid)
EB = [model.EB.get_values()[t] for t in T]
EB = np.asarray(EB)


p_batt = p_in-p_out
ess_size = model.ess.extract_values()['k_battery']
# ess = [model.ess.get_values()[t] for t in T]
# ess = np.asarray(ess)

print(model.ess)

# print(model.objective)


# printing all relevant parameters and variables for each index/hour
for i in range(len(p_batt)):
#     print(i,'\tp_out: %.1f \tp_in: %.1f \tp_batt: %.1f \tEB: %.1f \ttogrid: \
# %.1f \tsolar: %.1f \twind: %.1f'%(p_out[i],p_in[i],p_batt[i],RB[i],to_grid[i] \
# ,solar[i],wind[i]))
    print(i,'\tp_batt: %.1f \tEB: %.1f \ttogrid: %.1f \tsolar: %.1f \twind: \
    %.1f \tapx: %.1f'%(p_batt[i],EB[i],to_grid[i],solar[i],wind[i],apx_price[i]))

# Summary results Battery Model

# Creating list
revenue = []
revenue_windfarm = []

# Loop over indexes to obtain the revenues
for i in range(len(p_out)):
    revenue.append(to_grid[i]*apx_price[i])
    revenue_windfarm.append(wind[i]*apx_price[i])

# Creating dataframe to store all data
df= pd.DataFrame()
```

```
column_values1 = pd.Series(revenue)
column_values2 = pd.Series(revenue_windfarm)

# Insert column with correct name in dataframe
df.insert(loc=0, column='Revenue sustainable power station', value=column_values1)
df.insert(loc=1, column='Revenue wind farm', value=column_values2)


print('pv size (MWp)', solar_farm_size)
print('ess size (MWh)', ess_size)
print('ess size (MW)',max(p_batt))
print('outcome objective', value(model.objective))

sum_revenue = sum(revenue)
profit = sum_revenue - ((C_annualized_batt*ess_size) \
        + (C_annualized_solar*solar_farm_size))

print('Revenue sustainable power station',sum_revenue)
print('Profit sustainable power station',profit)

sum_revenue_windfarm = sum(revenue_windfarm)
profit_windfarm = sum_revenue_windfarm -(wind_farm_size*C_annualized_wind)

print('Revenue windfarm',sum_revenue_windfarm)
print('Profit windfarm',profit_windfarm)

# print(df.head(5))

# df.to_excel('WMW_model1_2018.xlsx', engine='xlsxwriter')
```

G Imbalance Model

Pyomo Code

```
## Python 3.0
# Import Libraries

import sys
import pandas as pd
from pyomo.environ import *
from pyomo.opt import *
import matplotlib.pyplot as plt
import numpy as np
import matplotlib.ticker as mtick
import math


# # ---------------------------------------- #
# apx_price = np.empty(8760)
# apx_price.fill(50.0)
# # ---------------------------------------- #

# print(apx_price)

## Imbalance Model
# The Imbalance Model penalizes every MWh of imbalance
# wind, solar PV power, and imbalance power per hour are used as input
# Further, the corresponding electricity price (APX) is used as an input.


# Reading solar, wind, and APX data into dataframe
path_complete = 'WMW_1mw_zon_final_2018.xlsx'
completeData = pd.read_excel(path_complete)

# ---------------------------------------- #
# Input parameters
solar_farm_size = 50.0 #MWp
wind_farm_size = 144.0 #MWp
tau = 1.0 #hour (max c-rate)
EB_0 = 0.0 #start battery level
eta_in = 0.95 #charge efficiency
eta_out = 0.95 #discharge efficiency

# select range in the input data
tstart = 2000
tend = 2050
TT = tend - tstart
export_limit = 160.0

# Battery Capex per MWh
C_batt = 450000.0
Tlife_batt = 10.0 * 8760 #year * hours
C_annualized_batt = (C_batt*TT)/Tlife_batt

# Solar PV farm Capex per MW
```

```
C_solar = 520000.0
Tlife_solar = 15.0 * 8760 #year * hours
C_annualized_solar = (C_solar*TT)/Tlife_solar

# Wind farm Capex per MW
C_wind = 900000.0
Tlife_wind = 15.0 * 8760 #year * hours
C_annualized_wind = (C_wind*TT)/Tlife_wind

# penalty factor
rho1 = 5e2
rho2 = 1e-3
alpha = 3.6 # Imbalance penalty in EUR/MWh^2

# ---------------------------------------- #
# converting different timeseries to lists
apx_price = np.array(completeData['apx_price'].tolist()[tstart:tend])
solar = np.array(completeData['solar_new'].tolist()[tstart:tend])*solar_farm_size
# wind = np.array(completeData['wind_power'].tolist()[tstart:tend])
wind = np.array(completeData['WMW_real'].tolist()[tstart:tend])
imbalance = np.array(completeData['wmw_imbalance'].tolist()[tstart:tend])

T = list(range(solar.shape[0]))
# computed optimal battery size in MWh
K = ['k_battery']

# print(completeData.head(5))

# Declare Concrete Model
model = ConcreteModel()
# model.t = Set(initialize=T, doc='Timesteps')
# model.I = RangeSet(1, 30)
# model.I = Set()

# loop over input parameters /indexeren
apx_price_dict = {t:apx_price[t] for t in T}
solar_dict = {t:solar[t] for t in T}
wind_dict = {t:wind[t] for t in T}
imbalance_dict = {t:imbalance[t] for t in T}


# ---------------------------------------- #
# Setting all input parameters
model.apx_price = Param(T, initialize=apx_price_dict, doc = 'APX Price (EUR/MWh)')
model.p_solar = Param(T, initialize=solar_dict, doc = 'Solar power (MW)')
model.p_wind = Param(T, initialize=wind_dict, doc = 'Wind power (MW)')
model.p_imbalance = Param(T, initialize=imbalance_dict, doc = 'Imbalance power (MW)')

# ---------------------------------------- #
# Setting all variables
model.to_grid = Var(T, bounds=(0.0,export_limit), doc = 'Export power (MW)')
model.p_in = Var(T, bounds=(0.0,np.Infinity), doc = 'Charging power (MW)')
model.p_out = Var(T, bounds=(0.0,np.Infinity), doc = 'Discharging power (MW)')
model.EB = Var(T, bounds=(EB_0,np.Infinity), doc = 'Battery Level (MWh)')
model.ess = Var(K, bounds=(0.0,np.Infinity), doc = 'Storage size (MWh)')
model.curt = Var(T, bounds=(0.0,np.Infinity), doc = 'Curtailed Power(MW)')
```

```
# ---------------------------------------- #
# Setting up all constraints
# upper and lower battery level limit
# the battery level (EB) cannot be lower than 0.1, and above 0.9 times
# the battery capacity (k_battery) computed
def EB_upper(model,t):
    return model.EB[t] <= 0.9 * model.ess['k_battery']
model.upper_max = Constraint(T, rule=EB_upper, doc = 'E_batt upper limit')

def EB_lower(model,t):
    return model.EB[t] >= 0.1 * model.ess['k_battery']
model.lower_max = Constraint(T, rule=EB_lower, doc = 'E_batt lower limit')


# Maximum charging and discharging power limits
# the maximum charging and discharging power are the battery capacity found in MWh
# divided by tau in hours
def p_in_max(model,t):
    return model.p_in[t] <= (model.ess['k_battery']/tau)
model.p_in_max = Constraint(T, rule=p_in_max, doc = 'Maximum power in')

def p_out_max(model,t):
    return model.p_out[t] <= (model.ess['k_battery']/tau)
model.p_out_max = Constraint(T, rule=p_out_max, doc = 'Maximum power out')


# Battery level equation
# the battery level starts at soc_0
# at each index the previous energy in the battery is summed by the energy what needs
# to be stored during the charging scenario. During discharging the power out of
# the battery is substracted from the previous energy stored in the
# battery (battery level).
def Battery_level_rule(model,t):
    if(t == 0):
        return model.EB[t] == soc_0 + eta_in*model.p_in[t] \
        - (1.0/eta_out)*model.p_out[t]
    else:
        return model.EB[t] == model.EB[t-1] + eta_in*model.p_in[t]\
        -(1.0/eta_out)* model.p_out[t]
    model.state_equation = Constraint(T, rule=Battery_level_rule, \
                                    doc = 'Battery level equation')

# Balance of system equation
# the balance rule ensures that the system is never pulling electricity from
# the grid when wind power and solar power combined are above the power to the
# grid (cable capacity limit) this can flow in the battery system by power_in.
# When the combined generation is lower than the cable capacity the battery can
# discharge via power_out.
def balance_rule(model,t):
#     return -model.to_grid[t] - model.curt[t] + model.p_out[t] - model.p_in[t]
#     + model.p_wind[t] + model.p_solar[t] == 0
    return -model.to_grid[t] + model.p_out[t] - model.p_in[t] + model.p_wind[t]\
    + model.p_solar[t] == 0.0
model.balance_equation = Constraint(T, rule=balance_rule, doc='Load balance')
```

```python
# Objective function
# maximize profit by selling electricity to the grid and penalizing
# p_imbalance by Alpha rho1 prevents the model from charging and discharging
# at the same time
def objective_rule(model):
    output =  sum(model.apx_price[t]*model.to_grid[t] for t in T)\
    - (C_annualized_batt*model.ess['k_battery'] + C_annualized_solar*solar_farm_size)\
    - alpha *sum((-model.p_out[t] + model.p_in[t] - model.p_imbalance[t])**2 for t in T)\
    - sum((rho1*model.p_out[t]*model.p_in[t] for t in T))
    return output
model.objective = Objective(rule = objective_rule, sense=maximize, \
                            doc='Objective function')



def pyomo_postprocess(options=None, instance=None, results=None):
    model.objective.display()


# ---------------------------------------- #
# Specifying the Solver
solver = SolverFactory('ipopt')
# changing the max. number of iterations of the solver
solver.options['max_iter']= 15000
# printing the solver results
solver.solve(model).write()
#---------------------------------------- #

p_in = [model.p_in.get_values()[t] for t in T]
p_in = np.asarray(p_in)
p_out = [model.p_out.get_values()[t] for t in T]
p_out = np.asarray(p_out)
to_grid = [model.to_grid.get_values()[t] for t in T]
to_grid = np.asarray(to_grid)
EB = [model.EB.get_values()[t] for t in T]
EB = np.asarray(EB)


p_batt = p_in-p_out
ess_size = model.ess.extract_values()['k_battery']
# ess = [model.ess.get_values()[t] for t in T]
# ess = np.asarray(ess)

print(model.ess)

# printing all relevant parameters and variables for each index/hour
for i in range(len(p_batt)):
    print(i,'\tp_batt: %.1f \tEB: %.1f \ttogrid: %.1f \tsolar: %.1f \twind: %.1f \
    \timb: %.1f \tapx: %.1f'%(p_batt[i],EB[i],to_grid[i],solar[i],\
                              wind[i],imbalance[i],apx_price[i]))
```

```python
# Summary results Imbalance Model


# Creating lists
p_imbalance_after_optimization = []
p_imbalance_before_optimization = []
revenue = []
revenue_windfarm = []
cable_usage = []
cable_usage_wind = []

# Loop over indexes to obtain the revenues
for i in range(len(p_out)):
    p_imbalance_after_optimization.append(p_batt[i]-imbalance[i]) # remaining imbalance
    p_imbalance_before_optimization.append(imbalance[i]) # inital imbalance
    revenue.append(to_grid[i]*apx_price[i]) # sum of revenue from whole system
    revenue_windfarm.append(wind[i]*apx_price[i]) # sum of revenue of wind farm only
    cable_usage.append(to_grid[i]/export_limit)
    cable_usage_wind.append(wind[i]/export_limit)

# Creating dataframe to store all data
df= pd.DataFrame()
column_values1 = pd.Series(p_imbalance_after_optimization)
column_values2 = pd.Series(imbalance)
column_values3 = pd.Series(apx_price)
column_values4 = pd.Series(wind)
column_values5 = pd.Series(revenue)
column_values6 = pd.Series(revenue_windfarm)
column_values7 = pd.Series(cable_usage)
column_values8 = pd.Series(cable_usage_wind)

# Insert column with correct name in dataframe
df.insert(loc=0, column='imbalance_filtered', value=column_values1)
df.insert(loc=1, column='imbalance unfiltered', value=column_values2)
df.insert(loc=2, column='apx price', value=column_values3)
df.insert(loc=3, column='wind power', value=column_values4)
df.insert(loc=4, column='Revenue sustainable power station', value=column_values5)
df.insert(loc=5, column='Revenue wind farm', value=column_values6)
df.insert(loc=6, column='cable usage', value=column_values7)
df.insert(loc=7, column='cable usage wind', value=column_values8)

## MAE after imbalance correction
df_abs = df.abs()
p_imbalance_after_optimization = df_abs['imbalance_filtered'].mean()
p_imbalance_after_optimization_nom = (p_imbalance_after_optimization/144.0)*100.0

p_imbalance_before_optimization = df_abs['imbalance unfiltered'].mean()
p_imbalance_before_optimization_nom = (p_imbalance_before_optimization/144.0)*100.0



# printing all relevant outputs
print('alpha \t\t\t\t\t\t\t\t', alfa)
print('pv size (MWp)\t\t\t\t\t\t\t', solar_farm_size)
print('ess size (MWh)\t\t\t\t\t\t\t', ess_size)
```

```
print('ess size (MW)\t\t\t\t\t\t\t',max(p_batt))


print('p_imbalance_after_optimization\t\t\t\t\t' \
      ,p_imbalance_after_optimization)
print('p_imbalance_after_optimization_nom(%)\t\t\t\t' \
      ,p_imbalance_after_optimization_nom)
print('p_imbalance_before_optimization\t\t\t\t\t' \
      ,p_imbalance_before_optimization)
print('p_imbalance_before_optimization_nom (%)\t\t\t\t' \
      ,p_imbalance_before_optimization_nom)
print('------------------------------------------------------------------')
print('outcome objective\t\t\t\t\t\t', value(model.objective))

mean_apx = df_abs['apx price'].mean()

sum_revenue = sum(revenue)
profit = sum_revenue - ((C_annualized_batt*ess_size) \
                        + (C_annualized_solar*solar_farm_size))
print('Revenue sustainable power station\t\t\t\t',sum_revenue)
print('Profit sustainable power station\t\t\t\t',profit)

sum_revenue_windfarm = sum(revenue_windfarm)
print('Revenue windfarm\t\t\t\t\t\t',sum_revenue_windfarm)

profit_windfarm = sum_revenue_windfarm -(wind_farm_size*C_annualized_wind)
print('Profit windfarm\t\t\t\t\t\t\t',profit_windfarm)


gain_imbalance_reduction = sum(imbalance - (imbalance-p_batt))*3.60
print('------------------------------------------------------------------')
print('gain_imbalance_reduction\t\t\t\t\t',gain_imbalance_reduction)

profit_with_imbalance_reduction = sum_revenue - ((C_annualized_batt*ess_size) \
                                                + (C_annualized_solar*solar_farm_size))\
                                                + gain_imbalance_reduction
print('!! TOTAL PROFIT !! \t\t\t\t\t\t',profit_with_imbalance_reduction)

# print(df_abs.head(15))
# print(df.head(5))
# df.to_excel('WMW_imbalance_alfa_36.xlsx', engine='xlsxwriter')
```

H Battery PV Model

Pyomo Code

```
## Python 3.0
# Import Libraries

import sys
import pandas as pd
from pyomo.environ import *
from pyomo.opt import *
import matplotlib.pyplot as plt
import numpy as np
import matplotlib.ticker as mtick
import math

## Battery PV Model
# The Battery PV Model determines the optimal BESS size in MWh (k_battery)
# and the optimal solar PV farm size in MWp (k_solar)
# wind and solar PV power per hour are used as input
# Further, the corresponding electricity price (APX) is used as an input.


# Reading solar, wind, and APX data into dataframe
path_complete = 'WMW_1mw_zon_final_2018.xlsx'
completeData = pd.read_excel(path_complete)

# ---------------------------------------- #
# Input parameters
solar_farm_size = ['k_solar'] #MWp
wind_farm_size = 144.0 #MWp
tau = 1.0 #hour (max c-rate)
EB_0 = 0.0 #start battery level
eta_in = 0.95 #charge efficiency
eta_out = 0.95 #discharge efficiency

# select range in the input data
tstart = 2000
tend = 2050
TT = tend - tstart
export_limit = 160.0

# Battery Capex per MWh
C_batt = 450000.0
Tlife_batt = 10.0 * 8760 #year * hours
C_annualized_batt = (C_batt*TT)/Tlife_batt

# Solar PV farm Capex per MW
C_solar = 520000.0
Tlife_solar = 15.0 * 8760 #year * hours
C_annualized_solar = (C_solar*TT)/Tlife_solar

# Wind farm Capex per MW
C_wind = 900000.0
Tlife_wind = 15.0 * 8760 #year * hours
```

```
C_annualized_wind = (C_wind*TT)/Tlife_wind
wind_farm_size = 144.0

# penalty factor
rho1 = 5e2
rho2 = 1e-3

# ---------------------------------------- #
# converting different timeseries to lists
apx_price = np.array(completeData['apx_price'].tolist()[tstart:tend])
solar = np.array(completeData['solar_new'].tolist()[tstart:tend])
# wind = np.array(completeData['wind_power'].tolist()[tstart:tend])
wind = np.array(completeData['WMW_real'].tolist()[tstart:tend])


T = list(range(solar.shape[0]))
# computed optimal battery size in MWh
K = ['k_battery']

print(completeData.head(5))

# Declare Concrete Model
model = ConcreteModel()
# model.t = Set(initialize=T, doc='Timesteps')
# model.I = RangeSet(1, 30)
# model.I = Set()

# loop over input parameters /indexeren
apx_price_dict = {t:apx_price[t] for t in T}
solar_dict = {t:solar[t] for t in T}
wind_dict = {t:wind[t] for t in T}


# ---------------------------------------- #
# Setting all input parameters
model.apx_price = Param(T, initialize=apx_price_dict, doc = 'APX Price (EUR/MWh)')
model.p_solar = Param(T, initialize=solar_dict, doc = 'Solar power (MW)')
model.p_wind = Param(T, initialize=wind_dict, doc = 'Wind power (MW)')


# ---------------------------------------- #
# Setting all variables
model.to_grid = Var(T, bounds=(0.0,export_limit), doc = 'Export power (MW)')
model.p_in = Var(T, bounds=(0.0,np.Infinity), doc = 'Charging power (MW)')
model.p_out = Var(T, bounds=(0.0,np.Infinity), doc = 'Discharging power (MW)')
model.EB = Var(T, bounds=(EB_0,np.Infinity), doc = 'Battery Level (MWh)')
model.ess = Var(K, bounds=(0.0,np.Infinity), doc = 'Storage size (MWh)')
model.pv = Var(solar_farm_size, bounds=(0.0,np.Infinity), doc = 'PV farm size (MWp)')
model.curt = Var(T, bounds=(0.0,np.Infinity), doc = 'Curtailed PV Power (MW)')
model.pv_out = Var(T, bounds=(0.0,np.Infinity),doc='PV output (MW)')

# ---------------------------------------- #
# Setting up all constraints
# pv_out (used solar power) is always equal or lower than the potential solar power
# where the potential solar power is p_solar (profile of a 1 MWp farm) times the solar
# farm size
```

```python
def pv_max(model,t):
    return model.pv_out[t] <= model.pv['k_solar']*model.p_solar[t]
model.pv_max = Constraint(T, rule=pv_max, doc = 'optimal solar farm size (MWp)')


# upper and lower battery level limit
# the battery level (EB) cannot be lower than 0.1, and above 0.9 times the battery
# capacity (k_battery) computed
def EB_upper(model,t):
    return model.EB[t] <= 0.9 * model.ess['k_battery']
model.upper_max = Constraint(T, rule=EB_upper, doc = 'E_batt upper limit')

def EB_lower(model,t):
    return model.EB[t] >= 0.1 * model.ess['k_battery']
model.lower_max = Constraint(T, rule=EB_lower, doc = 'E_batt lower limit')

# Maximum charging and discharging power limits
# the maximum charging and discharging power are the battery capacity found in MWh
# divided by tau in hours
def p_in_max(model,t):
    return model.p_in[t] <= (model.ess['k_battery']/tau)
model.p_in_max = Constraint(T, rule=p_in_max, doc = 'Maximum power in')

def p_out_max(model,t):
    return model.p_out[t] <= (model.ess['k_battery']/tau)
model.p_out_max = Constraint(T, rule=p_out_max, doc = 'Maximum power out')


# Battery level equation
# the battery level starts at soc_0
# at each index the previous energy in the battery is summed by the energy what needs
# to be stored during the charging scenario. During discharging the power out of
# the battery is substracted from the previous energy stored in the
# battery (battery level).
def battery_level_rule(model,t):
    if(t == 0):
        return model.EB[t] == EB_0 + (eta_in*model.p_in[t]) \
        - ((1.0/eta_out)*model.p_out[t])
    else:
        return model.EB[t] == model.EB[t-1] + (eta_in*model.p_in[t])\
        -((1.0/eta_out)* model.p_out[t])
model.state_equation = Constraint(T, rule=battery_level_rule,\
                                  doc = 'Battery level equation')




# Balance of system equation
# the balance rule ensures that the system is never pulling electricity from
# the grid when wind power and solar power combined are above the power to the
# grid (cable capacity limit) this can flow in the battery system by power_in.
# When the combined generation is lower than the cable capacity the battery can
# discharge via power_out.
def balance_rule(model,t):
    return -model.to_grid[t] + model.p_out[t] - model.p_in[t] + model.p_wind[t]\
    + model.pv_out[t] == 0.0
```

```
model.balance_equation = Constraint(T, rule=balance_rule, doc='Load balance')

# Objective function
# maximize profit by selling electricity to the grid and penalizing
# p_imbalance by Alpha rho1 prevents the model from charging and discharging
# at the same time
def objective_rule(model):
    output =  sum(model.apx_price[t]*model.to_grid[t] for t in T)\
    - (C_annualized_batt*model.ess['k_battery'] + C_annualized_solar*model.pv['k_solar'])\
    - sum((rho1*model.p_out[t]*model.p_in[t] for t in T))
    return output
model.objective = Objective(rule = objective_rule, sense=maximize, \
                            doc='Objective function')



def pyomo_postprocess(options=None, instance=None, results=None):
    model.objective.display()


# ---------------------------------------- #
# Specifying the Solver
solver = SolverFactory('ipopt')
# changing the max. number of iterations of the solver
solver.options['max_iter']= 15000
# printing the solver results
solver.solve(model).write()
#---------------------------------------- #

p_in = [model.p_in.get_values()[t] for t in T]
p_in = np.asarray(p_in)
p_out = [model.p_out.get_values()[t] for t in T]
p_out = np.asarray(p_out)
to_grid = [model.to_grid.get_values()[t] for t in T]
to_grid = np.asarray(to_grid)
EB = [model.EB.get_values()[t] for t in T]
EB = np.asarray(EB)
pv_out = [model.pv_out.get_values()[t] for t in T]
pv_out = np.asarray(pv_out)



p_batt = p_in-p_out
ess_size = model.ess.extract_values()['k_battery']
pv_size = model.pv.extract_values()['k_solar']


print(model.ess)

# printing all relevant parameters and variables for each index/hour
for i in range(len(p_batt)):
    print(i,'\tp_out: %.1f \tp_in: %.1f \tp_batt: %.1f \tEB %.1f \ttogrid: %.1f \
    \tsolar: %.1f wind: %.1f'%(p_out[i],p_in[i],p_batt[i],EB[i],to_grid[i],pv_out[i],wind[i]))

# Summary results Battery PV Model
```

```
# creating lists
revenue = []
revenue_windfarm = []


# loop over indexes to compute revenues
for i in range(len(p_out)):
    revenue.append(to_grid[i]*apx_price[i])
    revenue_windfarm.append(wind[i]*apx_price[i])

# Creating dataframe to store all data
df= pd.DataFrame()
column_values1 = pd.Series(revenue)
column_values2 = pd.Series(revenue_windfarm)

# Insert column with correct name in dataframe
df.insert(loc=0, column='Revenue sustainable power station', value=column_values1)
df.insert(loc=1, column='Revenue wind farm', value=column_values2)

# printing all relevant outputs
print('pv size (MWp)', pv_size)
print('ess size (MWh)', ess_size)
print('ess size (MW)',max(p_batt))
print('outcome objective', value(model.objective))

sum_revenue = sum(revenue)
profit = sum_revenue - ((C_annualized_batt*ess_size) + (C_annualized_solar*pv_size))
print('Revenue sustainable power station',sum_revenue)
print('Profit sustainable power station',profit)

sum_revenue_windfarm = sum(revenue_windfarm)
profit_windfarm = sum_revenue_windfarm -(wind_farm_size*C_annualized_wind)
print('Revenue windfarm',sum_revenue_windfarm)
print('Profit windfarm',profit_windfarm)

perc_curtailment = 100-((sum(pv_out))/(sum(solar*pv_size))*100)
print('curtailed solar power',perc_curtailment,'procent')
```