Hedging strategies to mitigate electricity price volatility exposure using storage units

Hedging strategies to mitigate electricity price volatility exposure using storage units

by

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This thesis does not mark the end of my student life. I believe that every day is a learning experience and it certainly does not mark the end of my journey in sustainability.

Contents

List of Abbreviations

RES	Renewable Energy Source
UN	United Nations
COP21	Climate Change Conference 21
GHG	Greenhouse Gas
EU	European Union
DER	Distributed Energy Resource
BESS	Battery Energy Storage System
ESS	Energy Storage System
TSO	Transmission System Operator
DSO	Distribution System Operator
IRR	Internal Rate of Return
NPV	Net Present Value
NaS	Sodium Sulphur
CAES	Compressed Air Energy Storage
U-PHS	Underground Pumped Hydro Storage
Li-ion	Lithium ion
MW	Megawatts
KWh	Kilowatt hour
O&M	Operation and Maintenance
DAP	Day-ahead Price
MA	Moving Average
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
ACF	Auto-Correlation Function
PACF	Partial Auto-Correlation Function
ARIMAX	Autoregressive Integrated Moving Average with exogenous variables
SARIMA	Seasonal Autoregressive Integrated Moving Average
SARIMAX	Seasonal Autoregressive Integrated Moving Average with exogenous variables

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Executive Summary

The ambitious energy policy goals set by the European Union have accelerated the pace at which energy efficiency and clean energy measures are being adopted. The Netherlands, lagging behind by a massive margin in transitioning to a green energy infrastructure, feel the need, now more than ever, to push the integration of renewable energy into the grid.

The state of the electricity industry has remained almost the same ever since its inception, but has undergone relatively significant changes in the past two decades. The main advancements being decreasing costs of clean energy technologies like solar panels and storage solutions, increasing electricity demand, changing policy & regulations to achieve decarbonization and the active attempt to phase out fossil fuel energy sources like coal. However, changing the energy mix in the electricity grid is bound to make grid management more cumbersome, owing to the intermittency posed by the renewable energy sources and their lack of flexibility, leading to extreme volatility in the electricity market prices. The inertial characteristics of the heavy rotating masses of fossil-powered plants allow traditional power plants to provide flexibility in the grid. Flexibility, in this thesis, is defined as the system's ability to respond to uncertain generation and demand, while maintaining a constant energy balance. Inertia, in the simplest terms, refers to the resistance provided by an object to a sudden change in motion. As renewables begin replacing conventional power plants, the flexibility required will have to be provided by solutions that allow the electricity generated from the renewables to be stored and used later, which also provides an avenue to hedge the risks from volatile electricity prices. Energy Storage is identified by the Dutch government as one of the most important techniques to provide flexibility surpassing alternatives like Demand Response and Energy Efficiency.

This thesis proposes a new approach to design a hedging strategy using energy storage systems. It aims to hedge the risks arising from daily price volatility in the electricity market, that the various stakeholders in the distribution grid are subjected to, caused by factors like increasing grid penetration of renewables, increasing carbon prices etc. "Hedging" in this study, is the act of risk aversion by taking a certain action in the present to avoid a future consequential risk.

The ability to store electricity after purchasing from the wholesale market, when looked at from an economic point of view, directly points to being able to store electricity when its in excess (accordingly also cheapest) and to sell it when it is most expensive. This is referred to as "energy arbitrage via electricity prices" and is carried out in the research presented in this work. Along with arbitrage, the strategy also proposes the idea of also being self-sufficient during period of high electricity prices. The significance of emphasizing electricity prices in the term "energy arbitrage via electricity prices" is because energy arbitrage can also be used for technical services like peak shaving that looks into the capacity constraints of the grid, which is beyond the scope of this thesis. The scope of this thesis is to find an analytical approach to design a hedging strategy, to monetize on volatility in the day-ahead electricity market to its maximum potential, for the stakeholders like energy suppliers (that do not own generation assets) in the distribution grid.

Electricity markets are known to be much more volatile than other commodity markets like the stock market [29]. Rising grid penetration of renewables will only increase this volatility and affect most the parties present in the distribution grid. In the distribution grid, the main stakeholders are distribution system operators, energy suppliers and consumers. The consumers buy electricity at a fixed contractual price, in order to not face the risk that extremely volatile price peaks might pose.

This risk minimization definitely comes at a way higher price than what the consumer's energy consumption warrants in reality. The price at which the energy supplier or suppliers sells electricity to the consumer level, usually covers the risk that it faces due to the volatility at the wholesale level. The strategy based on hedging, proposed in this thesis, is an analytical approach aimed at mainly hedging the risks that the energy suppliers (i.e. private entities/arbitrageurs) in the distribution grid of a deregulated market will face in the event of high renewables grid penetration. In case this solution is not used, the communities will be exposed to the extreme volatility in the market. This strategy intends to prevent a transfer of risk to the consumer level, making the business model of the private entity more sustainable under competition and stable. The consumer in this thesis is an entire community (of around 20 households or a mixture of load-bearing entities that have a peak power consumption of 52kW) and the transaction is carried out between the energy supplier that owns the energy storage asset and the community. In this manner, the consumer can monetize from shielding itself from the most volatile price peaks, while allowing the service provider (i.e. the private entity) to make use of the least expensive prices.

In order to design a sustainable hedging strategy using storage units, four major milestones are reached, that emerged as a result of four supporting research sub-questions. The methodology and the outcome in each milestone is mentioned below:

- **The first milestone** entails an examination of the future electricity market domain, extending for the next 25 years (2019 - 2043). This is deemed necessary as a changing energy infrastructure would make the electricity market prices more volatile and modelling this volatility would make it easier to recognize the most appropriate hedging strategy using storage units. The electricity value chain of the Netherlands is thoroughly studied and day-ahead electricity market is chosen, mainly based on the fact that majority of the transactions take place in this market. The daily price volatility is then modelled, with the help of standard deviation calculations (as it is the recognized measure of volatility in any commodity market) based on the hourly electricity price that is predicted for the next 25 years, the latter done using a time series statistic model (ARIMA model) in R-programming. A measure of the different renewable energy sources affecting the future price volatility is also found.

- **The second milestone** can be seen as the most important as this helped in the development of the hedging strategy using storage units. Since the scope of this thesis is to build an analytical approach, probability distribution functions are chosen to do so. The price spread of each day is found to be fitting a normal distribution curve, which helps in estimating the number of hours that are the most attractive for energy arbitrage, forming the foundation of hedging strategy using storage units in this thesis. Upon several set of investigations, it is seen that energy arbitrage can be used to hedge the daily volatility induced by the points that are deviating by 1 standard deviation unit from the mean. The number of points is calculated to be 4 i.e. 4 hours in each case. This points to the fact that a 4-hour discharging/charging will enable an efficient functioning of the hedging strategy using storage units.

- **The third milestone** conducts a financial/business analysis of different project scenarios that an energy storage system used to hedge can create. The number of hours found in the second milestone is used to set a minimum limit on the energy storage size. Based on this limit, several energy storage technologies are investigated to finalize on lithium-ion battery energy storage system (Li-ion BESS) for the hedging strategy, to its extremely quick response time, falling costs and high system efficiency. It is then seen that, using financial economic metrics like Net Present Value and Internal Rate of Return, out of the three scenarios considered (a large scale of MW level, household scale of kW level, community scale of intermediate level), the community level would provide the best business model for the private entity that owned the Li-ion BESS.

- **The fourth milestone** offers a risk analysis of the hedging strategy using storage units. Risks can come in the form of unexpected grid penetration of renewables. In this case, the daily 24- hour price spreads may not necessarily follow a normal distribution and it exactly matches what is mathematically found. A risk assessment strategy is devised, which is explained in detail in Chapter 6, which drives the inception of an alternate hedging strategy using storage units. This new hedging strategy is designed using the Chebychev Theorem [102], that allows to estimate how many points can be utilized for energy arbitrage, if the hourly price spread does not follow a normal distribution. The hours that arise from the new strategy is then used for the financial/business analysis of the community level BESS project and it is seen that it will take a year longer to see returns if invested in this project.

There are several assumptions that are made throughout this study.

- In order to see how the different energy sources affect the prices, it was assumed that the entire energy produced is also consumed at real time, ignoring line-losses and other losses.
- In order to see how the hourly penetration of these different sources affects the hourly price, an expected increase or decrease in percentage is also applied across each hour, assuming that an annual percentage increase or decrease in renewables will be distributed uniformly across each hour as well.
- The private entity incorporating the hedging strategy will use the long term hourly forecast until 2043 to make investment decisions of the BESS project, but they will carry out short-term forecasts closer to real-time transactions, each day, to be able to implement the hedging strategy.
- The needed policy and regulations will be designed in the future electricity market.
- This hedging strategy is that it is applied to only one node and is confined to a small-scale application and not for a transmission level application.

To the best of the knowledge conveyed via this report, it is evident that this hedging strategy using storage units envisions to either complement traditional hedging instruments like financial contracts or completely replace them. Hedging strategy using storage units guarantees to provide a more dynamic risk aversion compared to the traditional contracts, as it is performed on a day-ahead basis, rather than relying on a fixed price for set intervals of time. In the case of an unforeseen and unusual spike in prices, this hedging strategy allows to make transactions closer to real-time than in the case of financial contracts. The hedging strategy also presents an alternate use by estimating the size of the energy storage that will be required. The sizing plays a key role in shedding light on the size of the consumer and which energy storage option would make the most financial sense.

This hedging strategy has an industrial relevance, as it proves to be an ideal solution that a consulting company can offer to an entity that acts like an energy supplier or is an entity that is looking to enter the electricity market with the aim of owning an energy storage asset. The economic/business/financial analysis strengthens this solution.

The hedging strategy has a scientific relevance, as it uses a simplified technique of using probability density functions to propose the number of hours that a BESS discharging/charging will be the most profitable during hourly energy arbitrage in a highly volatile, renewable energy rich market. Unlike other studies, this study utilizes future daily price volatility. It also allows the entity that implements this strategy to quantitatively analyze where in the distribution grid this strategy will be the most economically feasible. This study forms a basis for future scientific research, which includes optimizing the contribution by variables (especially technical parameters like system efficiency, power rating, energy capacity etc.) that have been used in the break-even analysis to see the reach of the strategy and energy arbitrage can be used along with technical feasibility to make a sound case for energy storage systems.

There are several ways in which the accuracy of the findings in this report could have been improved. Some include access to more historical price data and a more complex and detailed price prediction model. From an institutional point of view, if the electricity markets in Europe are made as accessible and open as the markets in the United States (like the PJM market), this strategy could be more relevant. This strategy only forms a base for a solution, but a detailed optimization model has to be designed to see what other factors can be taken into account and if the strategy can be used, once all possible factors are considered.

Kritika Karthikeyan
Delft, August 2019

1 Introduction

1.1 Problem Orientation

The energy infrastructure across Europe is undergoing significant changes. The share of RES like solar and wind in the Dutch power generation mix has increased quickly in the last decade. This was driven by the various targets set by the government of the Netherlands that was a result of signing several international agreements, such as the 1992 UN Framework Convention on Climate Change (the foremost climate treaty) and the Kyoto Protocol (enlisting different GHG emission reduction for different countries) in 1997. In 2015, the Netherlands also agreed to adhere to the terms of the UN's COP21, commonly known as the Paris Agreement, the main aim being to keep the global temperature rise well below 2 degree Celsius. Having failed to reach any of the targets for 2020 proposed in any of the international and national climate treaties, the Dutch government now plans to reduce its GHG emissions by 49% by 2030, with respect to the 1990 levels and aims at a reduction of 79% in 2050, compared to its 2015 levels [1] [2].

One of the ways through which the Netherlands plans to meet its targets is by decarbonisation and shifting its reliance from fossil fuels to more RES, at a faster rate compared to the last decade. The share of renewables in the grid stands at around 7% as of early 2019. By 2023, the government wants to push for 16% of renewable energy in the grid [3]. By 2030, the Dutch government aims for RES to contribute 70% of electricity production so as to achieve a 49% target of carbon emissions in comparison with the 1990 levels [4]. This will be highly demanding for the grid as well as society. The per capita electricity consumption of NL in 2017 was 14% more, compared to the rest of the EU, due to the presence of large-scale industries like petrochemical and oil refineries [5]. Intermittent RES having to cater to the increasing demand will make energy transition more complex.

In reality, a sudden increase in the share of renewable energy generation won't be as promising and straight forward as it sounds. There are various issues that will accompany this change, on both technological level in maintaining grid stability as well as institutional level in organising electricity markets. There will be a higher requirement for flexibility within the power system infrastructure. Integrating more renewables will increase the generation uncertainty and an accurate prediction of available solar or wind energy for the next day will be an issue. This will mean that the imbalances in the system will be high, which means that the system operators will need to reserve enough flexibility or capacity in order to deal with these imbalances [6].

Flexibility here, refers to the ability of the system to respond to unpredictability in generation and demand, while maintaining a constant balance between them. In traditional power systems, supply follows demand, with the system operators having knowledge of how much to generate to meet a certain load. These system operators are also able to control the energy sources, i.e. traditional power plants have synchronous generators that can be ramped up and down depending on the needs of the grid. This is how flexibility in the power system is provided conventionally, with synchronous generators supporting the maintenance of voltage and frequency around nominal values [7]. Renewable energy plants like solar or wind, do not have synchronous generators and are intermittent in nature, posing a severe threat to security of supply [7]. This intermittency will also have drastic effects on the prices in the electricity market. For example, the renewable energy (wind and solar) contribution to the electricity generation mix in 2017 was 53% in Denmark and 26% in Germany and this would leave general public under impression that the electricity prices would have decreased accordingly, but it is quite the opposite [7]. The Danish and German electricity markets are the first and second most expensive among the EU states respectively. The intermittency of RES is found to be the root cause of these rising electricity prices [7]. This unpredictability leads to excess electricity produced when not needed and not enough when the demand is high. This in turn leads to solar and wind dependent countries like Germany and Denmark relying on their neighbouring states to buy electricity to meet their national demand, which leads to increasing price volatility. Cross border exchange is not the only reason for electricity price volatility, but also factors like fossil fuel prices, carbon prices and weather conditions.

Financial and econometric approaches are used in this thesis (by making use of electricity pricing), while also proving this to contribute towards a physical solution (by providing flexibility). Since any project or solution in the area of energy transition boils down to whether it can reduce costs incurred by the parties that will be on the consuming end of this solution, this study intends to find a strategy that will not only monetize on the price volatility but also provide stakeholders on whether an investment with the use of this strategy will make financial sense.

1.2 Problem Definition

As the RES increase and start becoming one of the main generation sources, there will be a substantial change in the way electricity prices behave. The successful degree to which deregulation has been executed together with the targeted goals of decarbonisation, has increased the share of decentralised generation capacity. The share of generation from DERs is expected to exceed 30% by 2030 in the EU and could account for more than half the installed generation capacity by 2050 [8]. This will result in the display of erratic behaviour by electricity prices. The intermittency portrayed by the RES and the non-storable nature of this electricity, will lead to fluctuating electricity prices, with higher occurrence of price jumps, leading to an increase in price volatility. The exposure of market stakeholders to this increased volatility and thereby increased uncertainty, will affect a quick transition to clean energy. This acts as a main driver for investigating different methods that are implemented to curb this type of uncertainty.

Hedging is the main technique used to reduce the exposure to volatility and reduce the risk from uncertainty in any commodity market. Hedging can be simply explained as an action taken today to benefit from tomorrow. To elaborate this definition, consider an example common in the airline industry, where fuel is purchased at an agreed upon price using a contract for the next few years, so that the airline company does not get affected by the volatile fuel prices. This is possible as suppliers in commodity markets like petroleum, have inventories that allow intertemporal arbitrages, which enables matching between supply and demand portfolios [9]. In electricity markets, there is an evident uncertainty about how much electricity will be drawn by the consumers. In usual electricity contracts, market players in the distribution grid, like suppliers, have the commitment to serve and cannot cut down on delivery, unless the nature of contract is “interruptible” [9]. Despite how the suppliers hedge expected demand, they will fall long or short given demand stochasticity and further compensation will be done at volatile electricity market prices, putting the suppliers’ profits at risk. There is an uncertainty at the supply side as well, given the unpredictability posed by the renewables and lack of cost-effective storability.

Existing contractual strategies are applicable to the power system in its current state. These contracts include bilateral and over-the-counter contracts that are usually agreed upon over a fixed price for a certain interval. Given the rate at which RES want to replace current fossil fuel baseload generation, market players will have to engage in strategies that are more dynamic, depending on the kind of electricity market (i.e. if it is for a day-ahead market, the strategy should be adaptable for at an hourly level). Hedging with contractual instruments may not prove to be the most efficient in renewables rich energy market, especially using linear payoff instruments (the derivative contracts that shift one-for-one with changing price or rate) like forward and futures contracts [10]. One of the major disadvantages in derivatives is the limited quantity of possible transactions, as it is confined by the terms of the contract. To manage this, an active strategy like the hedging strategy needs to be proposed.

There is a clear distinction between the terms energy arbitrage and price hedging. Hedging is an act of reducing exposure to volatile electricity prices, which is carried out using storage units. The methodology used to implement hedging is energy arbitrage. Energy arbitrage utilizes varying electricity prices to buy/charge during low prices and sell/discharge during high prices, thereby monetizing volatility.

In order to give a clear understanding of what problem the hedging strategy intends to tackle, the following hypothetical practical example can be considered.

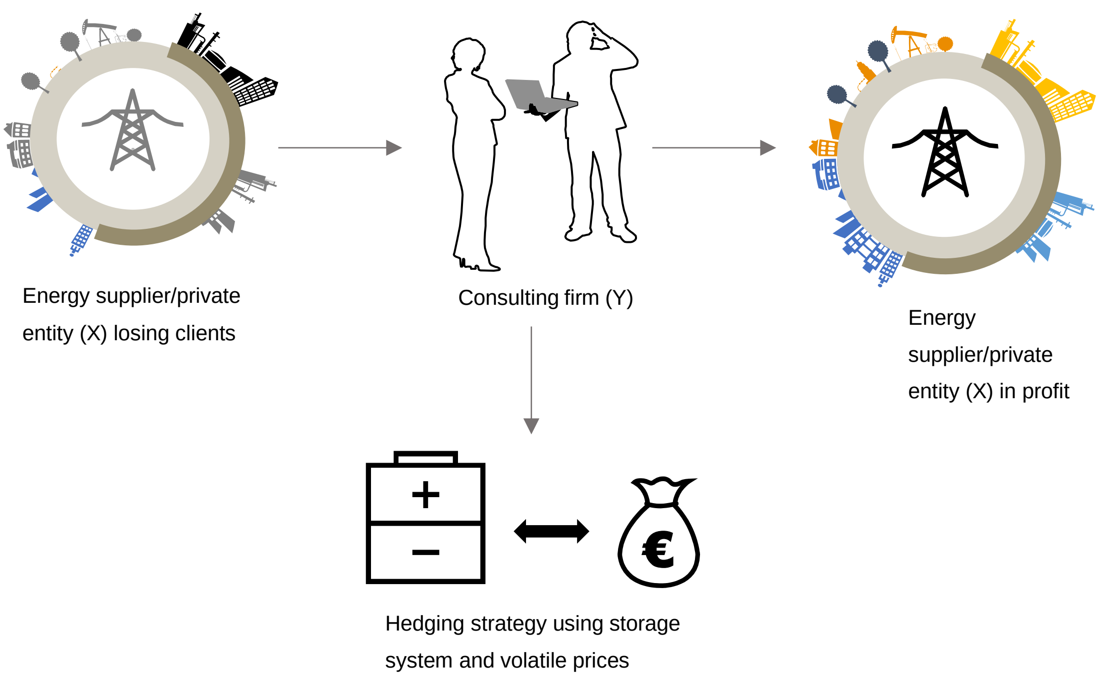

Figure 1: A hypothetical practical example of the usage of the hedging strategy

An electricity supplier/supplier, X, in charge of a community, approaches a consulting company, Y, after having encountered a decrease in revenue and stagnation of profits. X identified the problem to be customers switching to other retail companies due to its higher contract prices in comparison to other companies. It forecasted this issue to persist once the Netherlands moves closer to their renewable energy targets, as this would mean heightened price volatility at the wholesale electricity market. To tackle this issue, Y uses tools like electricity price forecast to come up with a dynamic hedging strategy, based on energy arbitrage. This dynamic hedging strategy requires X to purchase a BESS that will initially complement the existing contractual agreements and later completely replace them. Y also provides X with a complete analysis of which BESS to invest in. This hedging strategy allows Y to narrow down their clientele and realize where in the energy infrastructure of the distribution grid, will this strategy make the most economic sense.

This study will use ESSs for hedging electricity price volatility, which can be termed as "physical" hedging or hedging using storage units, which will be approached by answering the research questions specified in the upcoming sections of this chapter.

1.3 Research Goal

The goal of this research is to fill the gaps caused by limited research on limiting price volatility using demand response, when compared to the demand response studies that focus on reducing system costs and increasing system reliability. The price-based demand response programs usually push the variations in the wholesale market directly on to the consumers, allowing them to enjoy low prices but also suffer the consequences of extremely high prices (which is usually more probable than low prices in a renewables rich electricity market) [11]. A trade off that the consumer has to make while indulging in demand response programs is the inability to not have full control over their flexible loads, since the timing of these loads are used to monetize on the low price intervals [11]. The main objective of demand response optimizations is usually reduction of system costs and a customer's willingness to pay entails only a small portion of it [11]. The mitigation of price volatility is an added bonus of such programs. The results of the hedging strategy proposed in this thesis can be coupled with reduction of overall costs to allow the demand response optimization programs to consider mitigation of price volatility with more significance. This strategy investigates the impact of the chosen storage technology in hedging against price volatility and examines the appropriate size of the storage unit, with volatility mitigation as its main objective.

This thesis uses the multidisciplinary features of power systems, like electricity markets or storage technologies, to arrive at conclusions that are more holistic and aim at a higher integrated-system level. It does not intend to deepen the knowledge in data forecasting, electricity markets or different kinds of storage technologies but focuses on various related sections that may give rise to future highly specialized research work. It explores the various cross-sections of electricity markets and storage to come up with a novel hedging mechanism based on electricity price volatility. The section of the electricity market in focus in this report is the day-ahead market. Day-ahead electricity markets trade electricity on a day-to-day hourly basis, is the chosen electricity market in this research, owing to the 80% of the energy that is traded out of all the markets [12].

The main objective of the research is to use energy arbitrage based on day-ahead electricity pricing to hedge the risks and the objective behind the methodology is to create a power market design that hedges electricity prices by using storage technologies in periods of low and high peak prices at different levels in the distribution grid, thereby reducing the exposure to price volatility. Volatility in the electricity market is a reflection of the power system behaviour in attempting to maintain the balance between generation and demand.

Probability distribution of hourly electricity prices is utilized to attain the objective. The reason behind using probability distribution functions is to understand how many peak and off-peak prices should be considered for energy arbitrage. This study can be extended by applying more complex forms of normal distribution function like Gaussian mixture, but that goes beyond the scope of this thesis. Given the strong analytical reformulation properties of Gaussian distribution and given how well-studied this probability distribution is, it can easily be applied to more complex distributions, provided that the complex distributions are able to provide a percentage of area under the curve (like how the empirical formula does). The methodological contribution of this thesis is to design an analytical strategy that will enable a private entity to make business decisions using probability distribution of hourly electricity prices. These decisions will be targeted to reduce its exposure to volatility as well as generate income using volatility. This is mainly done by using long-term price forecasts to gauge whether investing in a storage technology at a certain level in the distribution grid will be economically feasible. Using short term day head forecasts, the private entity that owns the storage technology can get a more accurate idea of when to buy and sell electricity. This is backed with scenario analyses, econometric analyses and a risk analysis, which gives a clear understanding of the different drivers that influence economic viability of energy storages and help in making a sound investment decision, using various profitability measures. It also provides a basis for further research that can be carried out using optimization models where both technical as well as cost factors can be optimized.

1.4 Research Questions

The main research question is as follows:

What hedging strategies using storage units at the distribution level, that enable price volatility mitigation in the coming 25 years, can be formulated?

This question can be answered using four sub-questions:

1. What does the electricity market domain resemble in the next 25 years (i.e. 2019-2043)?

   This sub-question provides insights into the trend that the electricity prices will follow in the next 25 years. This domain will change drastically with the increase in renewables in the grid and there is currently no standard set of forecasts used across the research work. Hence, for the purpose of this study, the hourly electricity prices are forecasted until 2043. This study focusses only on the day-ahead electricity market in the Netherlands, hence the need to forecast hourly electricity prices. Using the forecasts, electricity price volatility at an hourly level is modelled until 2043, which will the basis of this thesis.

2. Which hedging strategy purely based on electricity prices is the most economically feasible?

   This sub-question first investigates if it is possible to design a hedging strategy using storage units that will gradually replace traditional contractual hedging. Upon the investigation reaching a conclusion that such a hedging with the help of a BESS is possible, an analytical hedging strategy is then designed based on probability distribution functions of hourly electricity prices on a daily basis. The accuracy of the strategy is heavily correlated with the third research question.

3. At what level in the grid and using which storage technology, can the proposed hedging strategy be used?

   An answer to this sub-question is derived from the strategy derived in sub-question 3. The strategy is used to obtain a high level understanding of the minimum battery size based on the charging and discharging hours that can be fitted at any level in the distribution grid. Three levels are chosen –

at the large scale distribution level, at a community scale and at a household scale. Based on an economic, breakeven analysis of BESS of different sizes based on the discharging/charging hours implied by the proposed hedging strategy, the most suitable level is found. The placement is not random, but is a result of the most optimal business model selection based on technical and economic factors.

4. What risks will the private entity, providing the services, be exposed to?

   In order to understand the risks posed on the private entity that adopts the proposed hedging strategy, a sensitivity analysis based on changing RES penetration is carried out. The strategy is then tested on these altered parameters. In case it does not comply with the new parameters, an alternate strategy is designed and the risk posed by the new hedging strategy is investigated with respect to how economically feasible it is.

1.5 Research Methodology Flowchart

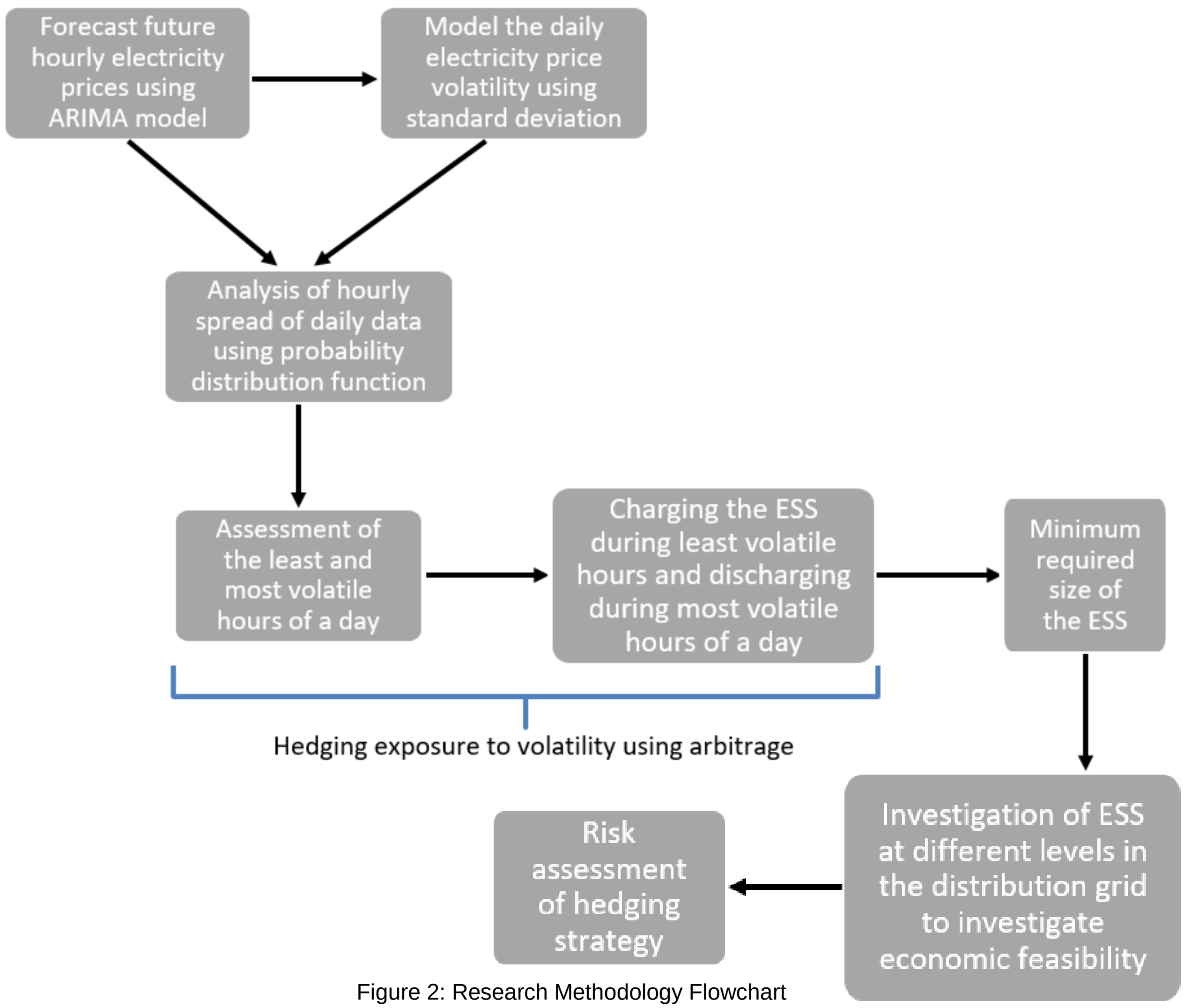

Figure 2: Research Methodology Flowchart

1.6 Story Ahead

This document is mainly divided into 7 parts, which follows the rhythm set by the research sub-questions. Chapter 2 presents a brief overview of the Dutch energy infrastructure and the Dutch electricity market design. This was deemed necessary to examine the different stakeholders that could be involved while designing the hedging strategy using storage units and to finalize on the most relevant ones. The market structure of the Netherlands is used to conceptualize the strategy that will work in a renewables rich Dutch electricity market of the future and also discusses the measures that the Dutch government intends to take to compensate for the flexibility that will be lost upon the discontinuation of traditional power plants. Chapter 3 conducts a simple hourly prediction of the electricity prices that will manifest in the day-ahead electricity market of the future. Historical hourly prices from 2014-2018 are utilized for this purpose. Relationship between the potential renewable energy sources that would penetrate the grid in the next 25 years, and hourly electricity prices is also studied. Chapter 4 displays all the aspects of the proposed hedging strategy – from the foundations of the strategy to its use in giving an estimate of the BESS size. Chapter 5 carries forward the work conducted in chapter 4 by utilizing the strategy to observe where in the distribution grid the hedging strategy will create the most financial benefit. The business model of this hedging strategy, based on the most value for money, is portrayed in this chapter. Chapter 6 assumes that the hedging strategy may not work at all times, given how unpredictable the future electricity market will be. A risk assessment is carried out based on varying RES penetration and an alternate strategy is proposed. This thesis is concluded in Chapter 7. It also provides recommendations on future work and provides a critical analysis of the work carried out.

2

State of the Dutch Electricity Infrastructure

This chapter gives an overview of the Dutch power system and the Dutch electricity market. It begins by an introduction to the current and future state of energy infrastructure in the Netherlands. It then discusses the Dutch electricity market design and its relevant elements that have a significant influence on the electricity prices. The need for an inclusion of more dynamic elements in the market design is touched upon, along with government-recognized solutions to do so.

2.1 The Dutch power system – today & tomorrow

The traditional electricity system was designed to cater to the supply and demand of the market with dispatchable sources of electricity i.e. the power plants that have the ability to adjust their power outputs delivered to the grid depending on the requirement. Dispatchable electricity generation include electricity from natural gas power plants (quicker dispatch speed of minutes to seconds) and thermal plants like coal power plants (slower dispatch speeds of hours). Since the discovery of Groningen gas field (the largest Dutch gas field even as of 2018) with a reserve of 2700 billion m^3 in 1950s, the Netherlands has been highly reliant on gas-fire power generation [13]. This trend got stronger with the discovery of sizable finds under the North sea. The Netherlands is the second-largest producer of natural gas in Europe, Norway being the first. However, the Dutch government limited the output from the gas field to 24 billion m^3 per year with a possibility of extracting 6 billion m^3 more in winters that are unusually cold [13]. The reasons behind this were increasing concerns about localized earthquakes due to gas extractions and to ensure security of supply; the Netherlands imported more natural gas in 2017 than it extracted domestically, denoting a major change in a long-established pattern. The Dutch electricity system, as of 2017, remains fossil fuel dominant, with a 35% reliance on coal as a source (35%) and a 46% reliance on natural gas [14]. However, global decarbonisation targets are facilitating the incorporation of RES into the power generation mix. Climate change has pushed majority of the nations to increase the share of renewable energy into the grid, considerably increasing their clean energy investment. Spain, for example, almost doubled the RES in their power generation mix from 28% in 2008 to 58% in 2013, on daily average. On some days, even up to 80% of the total production was contributed by RES [15]. The renewable energy share in the power generation mix of the Netherlands is increasing but at a very slow pace. As of 2017, 8% of the electricity was produced from wind energy and around 2% from solar.

Lagging behind compared to the rest of EU nations, the Netherlands is trying to take drastic measures to transition to clean energy. The Dutch government has decided to fully phase out power generation from coal and the gas field in Groningen by 2030 [16]. The carbon tax that is intended to be levied from 2020 onwards will make coal power unviable and will result in high wholesale prices. The baseload capacity will see a 60% contribution by wind and solar, while natural gas still accounting for 30% in the mix [16]. The dependency on a higher percentage of RES will also lead to an increase in electricity price volatility, which makes the findings of this thesis extremely relevant.

2.2 Evolution of the Dutch electricity market

Creating a unified electricity market has been on the European agenda from early 1990s. Prior to materializing this agenda, the government entities had a prominent share in various areas of the electricity market, forming monopolies especially within the generation sector. The last three decades saw an active liberalization of electric power sectors around the world. 'Economic liberalization' refers to the restructuring of government-controlled sectors to loosen control and state intervention, in order to foster increased private entity participation and economic development. The electricity market structure in the Netherlands, as we know it, is a result of a liberalization law that was passed in the late 90s, to promote fair competition among generators, to provide consumers the freedom of choice and to provide investment incentives to modernize the existing electricity infrastructure. The deregulation of electricity market followed a stepwise fashion, with the EU adopting policies over three directives. In Europe, these liberal reforms in the electricity market started as early as 1950s and 1960s [17]. The 1998 Electricity Act had a great influence over the liberalization of Dutch energy sector, which gave the producers and consumers more power to make the space of selling and buying electricity more sustainable, reliable, competitive and efficient. A major section of the consumers were able to choose their energy provider by 2002, the commercial consumers by 2004 and household consumers by 2008 [17]. Cross-border trade barriers were withdrawn, aiding the reduction of reserve capacity and generation costs through higher supply flexibility provided and efficient utilization of technologies with low marginal costs. The 1998 Electricity Act was modified several times, out of which one such amendment in 2008 took into account the distribution grids being fully ownership unbundled from the vertically integrated energy companies [18]. Emissions Trading Scheme (ETS) for electricity producers was introduced, which increased the opportunity cost of using carbon fuels. Further subsidies and tax schemes resulted in an increase in installation of clean energy technologies like windmills, solar panels and combined Heat & Power (CHP) [19].

The introduction of a competitive market place does come with its disadvantages. The market participants are now subjected to more uncertainty, and as a result, traditional contractual methods that were used as a method to shield against uncertainty, have also evolved. There is still a conflict about how to price these financial derivatives.

To examine the influence on electricity prices, it is also useful to examine the various interactions between different actors that engage in the electricity market, their primary function and mainly the relation between the technical and the economical elements. Electricity is a commodity with a real time need for production and consumption balance. Hence, the electricity market had to be designed and modernized in a way that this property always holds true. In the Netherlands, the electricity market comes very close to the textbook designed version of a liberalized electricity market (as shown in Figure 3) working in harmony, to ensure reliable and affordable electricity [20].

As shown in the Figure 3, different actors can manage different sections of the value chain, where the double-sided arrows represent possession of a specific actor over a certain section of the system and single-sided arrows represent the orientation of electricity trade. To understand how the physical and institutional (economic) layer are parallel, both these layers are clearly differentiated in Figure 3.

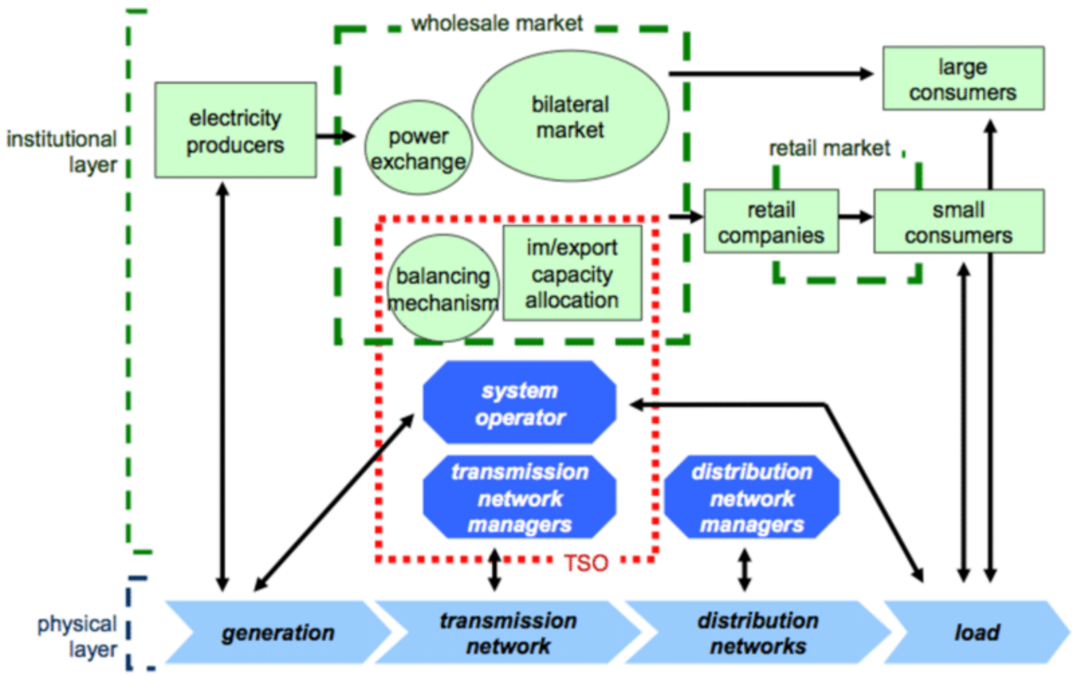

Figure 3: Electricity Value Chain in the Netherlands *[20]*

The Physical Layer

The physical layer, representing the technical aspects of the power grid, shows the flow of electricity, from the generators via high voltage transmission to the distribution networks via low voltage grids to the end consumers (both large-scale and residential level).

- Generation

The power generation mix in the Netherlands has always been largely dominated by fossil fuels. Netherlands remains far behind in the green energy transition. Netherlands has made considerable progress since 2004, but both the renewable energy target as well the speed of progress demanded for 2020 are over double. The poor ranking of 27 on 28 for its share of installed RES and an increase of only 0.4% from 2014 to 2016, has put the country under immense pressure to change their status.

There are mainly five generation entities in the Netherlands: Nuon (acquired by Vattenfall), Essent (acquired by RWE), Eneco, E.ON, and Delta, out of which the first four manage 55% of the majority installed capacity. The generation sector in Netherlands is completely deregulated and consists of 100% Independent Power Producers (IPPs).

- Transmission:

The wave of liberalization paved way to the establishment of TSOs, to control the bulk transmission of 220kV and 380kV grids. As the name suggests, TSOs run the transmission network and are responsible to operate a robust, cost-efficient, safe and reliable network. They are also in charge of providing security of supply to the consumers, avoiding frequency fluctuations, ensuring availability of reserve capacity, maintaining cross border connections and forecasting electricity demands for a medium time period [21]. TenneT operates the entire Dutch transmission grid, proving to be a state-controlled monopoly in the Netherlands. In order to promote market integration and to liberalize the gas and electricity markets within the EU, the third EU Legislative Package of 2009 set up an association of TSOs, ENTSO-E (European Network of Transmission Operators for Electricity), now comprising of 43 TSOs from 36 countries within Europe [22]. TenneT, in the Netherlands, is responsible for connecting the regional grids with each other and connecting the national grid with other EU states.

- Distribution:

Further unbundling led to the formation of DSO, that own and maintain medium and low voltage distribution grids. The unbundling forced the DSOs to be separated from being a part of energy producers, traders or suppliers and even from the transmission grid, which allowed access to the consumers in a non-discriminatory and fair way. The DSOs are responsible for the delivery of reliable and secure supply of electricity (or gas) to end-users. The emergence of DERs have forced the DSOs to diversify the services they offer. DERs are decentralized sources of energy like rooftop PV and micro wind turbines that act as active players in the electricity system and provide bilateral flexibility into the grid, which could increase congestion and unpredictability in the grid. Flexibility is defined as the ability of power systems to ensure a balance between generation and consumption and react quickly and reliably to substantial changes in supply or demand, in times of uncertainty. As opposed to the traditional service of merely connecting and disconnecting the DERs, DSOs now have to provide peak load management through DERs, network congestion management, provide reactive power and voltage support to TSOs, pose equal competitive conditions to various market players like aggregators, prosumers and other flexibility providers, establish avenues for flexibility, etc [23]. There are 8 electricity DSOs in the Netherlands, with three of them (Liander, Stedin and Enexis) covering majority of the country.

The DSOs in the Netherlands are regulated by ACM (Authority for consumers and markets). This authority has the ability to amend retail prices proposed by the suppliers if deemed to be unfair. In the Netherlands, the retail prices for industrial consumers decreased between 2008 and 2013, and increased for residential consumers due to increased grid costs and increased taxes. The industrial consumers, on the other hand, experienced decreased energy and supply costs which was offset by increased grid costs and constant taxes [24].

The Institutional Layer

The institutional layer represents the economic aspects of the power grid. In financial terms, electricity is a commodity that can be bought, sold or traded. The electricity market system, classified as long-term and short-term power markets, allows transactions involving electricity energy. Both producers and consumers establish the flow of load in the system by participating in the short-term power market, consisting of markets that can be bilateral, Over-the-Counter (OTC) or exchange-based, as seen in Figure 3 [8] [25]. The long-term trade can even go up to a year ahead and is shown in Figure 4 under "Forward and Futures Markets" [8] [25].

Wholesale market includes OTC and Exchange-based markets. There are usually two forms of OTC: bilateral and cleared. The largest volume of electricity, about 85%, is sold in the 'bilateral' market. This means that the electricity is sold directly by the generating companies/traders/supply companies to their customers via OTC contracts (a contract in which a mutual agreement has been made between the parties), that are kept confidential. The spot market (also referred to the day-ahead market in Europe) is of interest in this thesis, as the transactions in spot market are used to come up with the Hedging Strategy.

Figure 4 classifies the electricity market into various sub-markets, based on characteristics like purpose and time of delivery.

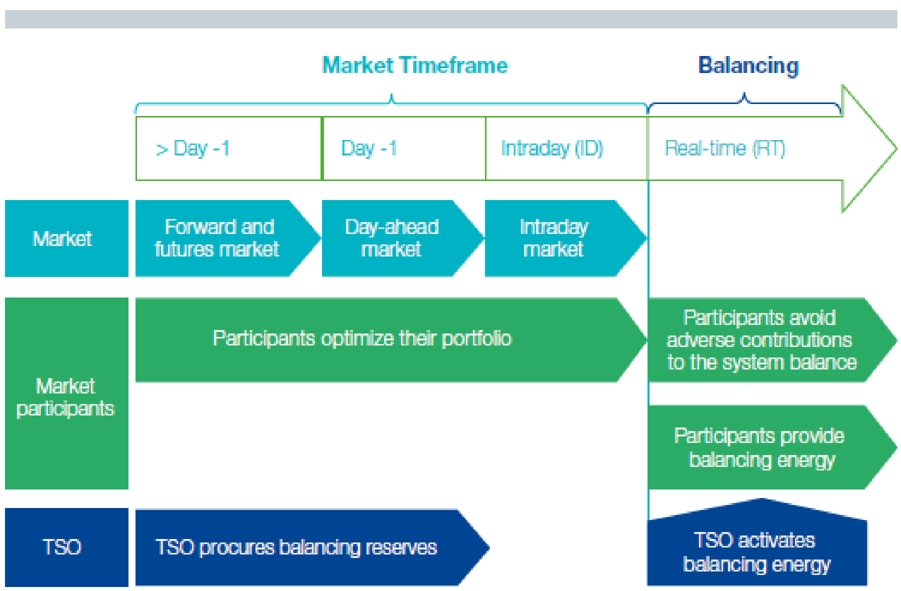

Figure 4: Electricity market in Netherlands at different timeframes *[28]*

A Power Exchange provides a platform to trade electricity, facilitating exchange through a clearing price that is set by the most optimal price at which the bids are offered by the producers and are bought by the consumers. The main aim of a power exchange is to provide a transparent and reliable avenue to exchange electricity physically and financially. An overview of the liberalized Dutch electricity market presented in [26], mentions Amsterdam Power Exchange (APX), owned by TenneT, as the power exchange in Netherlands. However, in 2015, the integration of the business activities of APX and EPEX SPOT, where day-ahead electricity transactions and intraday auctions can take place, completely diminished the influence of TenneT [27]. In a **day-ahead market**, both buyers and sellers can conduct transactions for physical delivery of electricity one day in advance. This market comprises the majority of the trading volume and has the maximum number of participants, hence the “electricity price” (always in €/MWh) mentioned in this report will refer to the day-ahead market price. In **intraday markets**, electricity is transacted on the same day. This market allows the market parties to make amends to their day-ahead nominations based on real time demand alterations, unforeseen power plant outages etc. [28].

Because electricity cannot be stored in the network, imbalances can cause the electricity system to become unstable and may result in large disruptions of service. Therefore all users of the Dutch electricity system (electricity producers supply companies and industrial consumers) work towards being ‘program responsible’ and are accountable in notifying the grid officials of their intended consumption and production. Program responsibility can also be exerted by authorized ‘program responsible parties’, that inform TenneT of their planned transactions for the following day and the networks they will use to carry electricity. The producers can offer reserve power, but they also pay if they generate less than that indicated in their energy programs. Consumers are forced to buy any power that they consumed in excess of their energy program in the balancing market, typically at prices higher than the spot market.

Since liberalization, electricity has gradually transformed into a commodity that is traded on markets based on short-term or long-term delivery financial contracts. Day-ahead markets, along with the others, are a part of the **wholesale market**, where the electricity prices are formed as a result of market clearing [28]. The clearing price for electricity in these wholesale markets is determined by an auction in which generation resources offer in a price at which they can supply a specific number of megawatt-hours of power. There are two kinds of electricity markets: wholesale and retail electricity markets. Electricity generators enter into competition in wholesale markets offering electricity at competitive prices to large consumers and electricity suppliers. **Retail markets** are platforms used by suppliers to sell electricity to end consumers [28].

Day-ahead market volatility can lead to substantial risks to market players, with the ones present at the generation side facing a risk on earnings due to low prices and consumers facing a risk of potential high prices. To avoid exposure to volatile prices in the electricity markets, market players take part in **financial contracts**, that lock a certain price for a certain interval of time. **Forward contracts**, traded on the Forward market, cover future payments based on trades that can occur from a year to few years of actual delivery ” [8] [25]. These contracts do not consider demand or supply constrains at the time of delivery, but legally agree to supply the amount agreed on the contract no matter what. **Options contracts** make it possible to indulge in Call-Option contracts where electricity can be bought for a pre-set price before the agreement expires and in Put-Option contract where electricity can be delivered at a pre-set price. Options contracts do not put an obligation on the investor to buy or sell while the contract is in effect, whereas a futures contract puts an obligation to do so.

These financial derivatives have evolved over time and tend to be more expensive as they take into account the rising gas prices (due to the shutting down of carbon-intensive power production) and an unpredictable rise in carbon prices (as regulators are constantly pushing to make CO2 pricing more stringent to give incentive to switch to green generation) [29]. These reasons, along with the high section of fluctuating power generation capacities, will only make electricity prices more volatile [29]. It is found that price volatility is a primary input into options pricing models (which is one of the financial derivatives used currently), pushing real costs onto consumers of electricity as power purchasing suppliers use costly options to hedge away from price risk [30].

Looking at all the aforementioned aspects of the economic layer of the electricity system proposed in Figure 3, there is a clear need for a more dynamic way to hedge risks against price volatility, which can be provided by ESS, through electricity price arbitrage. The physical layer, in addition to this, also requires an increased variability in energy generation, and the requirement to fully introduce and utilize flexibility in the grid can be done via a mechanism like energy storage and demand response.

2.3 Rising need for flexibility

Flexibility in power systems can be interpreted in many ways. In this thesis, it is defined as the ability to manage the variability and unpredictability of residual power load within the technical limits of power grid, balancing expected and unexpected imbalances in power supply and demand, in a matter of seconds to hours to months.

Due to a small contribution of RES and less unforeseen events, the need for flexibility is not currently that high in the Dutch power grid. Currently different power generation sources provide flexibility for demands that would occur at different timescales. For example, a coal-fired plant with a rated power between 100-1000 MW can respond to a demand that would require ramp-up/down time >30 minutes and gas-fired combined cycle plant with the same rated power can respond to a demand that would require ramp-up/down time <30 minutes [13]. Fuel cell and hydropower plants can respond almost immediately within their specific range of capacities. Solar panels and wind turbines bring in a lot of uncertainty as even though, say a solar panel, can respond immediately, it is subject natural fluctuations of solar insolation. Given the huge targets that the Netherlands wants to achieve, it will also have to make the contribution from variable renewable energy (VRE) sources very significant in the grid, and this will lead to an increasing need for flexibility. This need is predicted to double by 2030 and increase by a factor of 3 between 2030 and 2050. Another reason is the increase in total load arising from increase in electric vehicles (EV), heat pumps and other methods of electrification [3].

Among the various measures for providing sufficient flexibility, the following have been considered by the Dutch government as the most important.

- inter-country connections
- demand side management (DSM)
- decentralized storage
- thermal reserves provided by coal and gas

Energy storage (ES) acts a strong flexibility-providing source that adds notable economic benefits to various areas within the power system infrastructure, like providing an option to deal with uncertainty caused by RES and by reducing costs in areas like generation, transmission, distribution to system operation and balancing.

Utilizing ES can lead to several environmental and physical benefits. However, for it to have effective societal benefit, the parties interested in investing in this technology will have to be presented with a feasible business case that re-compensates them for their investments. Below is a list of the key services wherein ES plays a significant role, with respect to this thesis [31].

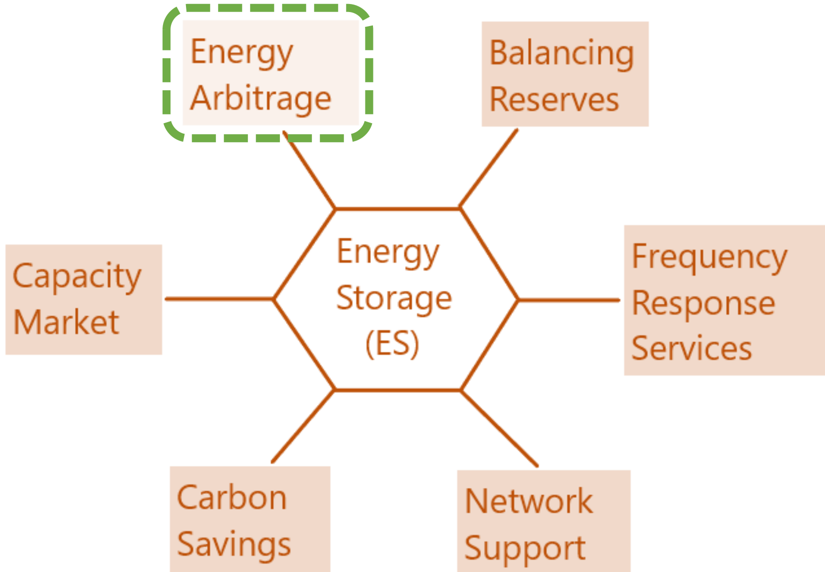

Figure 5: Energy storage (ES) services

Despite the fact that energy storage technologies can offer variety of services, from emission reduction to network support without expensive investments in grid infrastructure, and despite intensive research in this area and its ability to integrate RES, investment in energy storage, compared to RES, remains relatively limited. This is due to high capital costs associated with setting up a storage system and the lack of valuation frameworks. In most studies, capital costs and system capacity factor is disregarded while measuring economic performance [32].

In order to make this sector more attractive to investors, one of the many revenue streams of energy storage that provide value added services i.e. electricity arbitrage for distribution grid-scale energy storage, is studied in this report. The imbalances in electricity prices is monetized by taking part in day-ahead electricity markets, to discharge in times of peak electricity prices and charging when the electricity price is lower.

This thesis attempts at a more holistic approach for coming up with an arbitrage value and using that to decide the size of the ES, such that this will lead to the least error in sizing the system and reducing over expenditure. In order to reach a stage where the such a strategy can be designed, both long term and short term forecasting of the state of the day-ahead electricity market, by predicting the hourly prices, is necessary.

3

The Electricity Market Domain (2019-2043)

This chapter aims at providing a comprehensive view of what the electricity market domain would look like between 2019 and 2043. The main motivation behind understanding the future market domain is to see the trend that future electricity price volatility will follow, as the electricity prices are predicted to get more volatile with an increase in renewable energy grid penetration. The hourly electricity price volatility is modelled using forecasted hourly price, based on the trend followed by the historical hourly electricity price of the period between 2014 and 2018. A relation between the most relevant renewable energy sources that would be penetrated into the grid in the future and the price volatility is also found.

3.1 Data

This report studies hourly electricity price from the day-ahead market in €/MWh observations that covers the period from 01.01.2014 to 31.12.2018. This data was obtained from the ENTSO-E Transparency Platform, an online library for electricity power system data, which was established as a result of the “Transparency Regulation” (EU Regulation No. 543/2013) [33]. The data in this platform is provided by entities like TSOs and Power Exchanges. During literature review, it was found that there were datasets that were more extensive, with better quality and lesser gaps in information, available with external commercial parties, however due to financial and time constraints, the analyses shown in this report is based purely on the data retrieved from the Transparency Platform. The extra hour caused due to day light savings was looked over to maintain consistency as it was found to not pose a systematic problem when overlooked [33].

On analyzing the historical prices, it was found that the wholesale electricity price in the Dutch day-ahead market has dramatically increased. This increase was attributed to the increase in fuel prices and increasing assumptions about higher future CO_2 allowance prices. Between 2017 and 2018, the average electricity price saw a 33% increase (from 39.3 €/MWh to 52.5 €/MWh), which was higher than the 24% average increase in the entire Central Western Europe (CWE) region [34]. Prices were remarkably higher in the 2016/2017 winters than the previous winters due to the unusual cold spell. An unpredictable increase in the CO_2 prices is also expected to have a strong effect on the future price volatility [34]. In 2018, the total amount of imports significantly increased due to a decrease in total generation and this is reflected in the increased volatility in that period of Figure 6. After seeing a dip in the coal margins between 2016 to 2017 due to increasing carbon prices, this dip was less apparent in 2018. In the Netherlands, the natural gas prices influence the prices to a great extent as gas-fired plants set the price most of the times. In 2018, the gas plants increased the bids offered due to higher fuel costs, which offset the high price for coal-fired plants. The electricity consumption in the Netherlands increased in the spring months in 2018 more than usual (it usually remained in the same average as in 2011-2016) and it increased overall in 2018 compared to 2017 [34]. The gross decrease in generation, the net import increase and the net increase in electricity consumption led to a relative increase in day-ahead prices, which is seen in Figure 6.

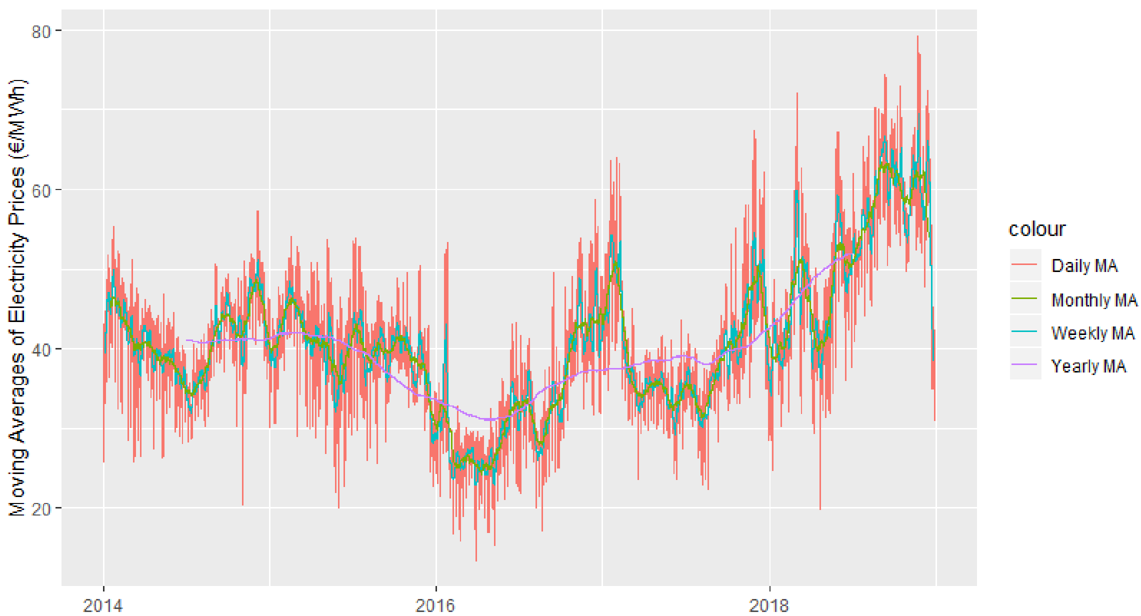

Figure 6: Increasing trend of day-ahead electricity prices in €/MWh

Liberalization has increased the liquidity of electricity markets, making recent historical electricity prices, generation and consumption portfolios, transmission flows and other previously hidden data, now publicly accessible. This can be exploited to study the effects of renewable energy shares on electricity prices and price volatility. An increase of RE share in the power generation mix has been found to reduce the average prices [35]. This trend is very prominent in Denmark, where increase in penetration of wind power in the day-ahead market has found to reduce the Danish electricity prices and the volatility [36]. The study conducted in [36] uses a non-parametric regression model to test this and to investigate the price levels and distribution of prices at different wind power levels, using hourly data of wind power forecast. The paper suggests that GARCH can also be used to model to study the impact of wind power on the price volatility in Denmark. Several other methods, like the ones shown in the following section, can be used to model and forecast electricity prices and dependent volatility as well.

3.2 Methodology of modelling hourly electricity prices

After reviewing the literature that surveys electricity price forecasting [37], it was found that the following five modelling techniques are commonly used:

- Multi-agent models – These models simulate the interactions between various agents like generating units and consumers, and design a price process by matching the market supply to demand. For example, Game theory and multi-agent simulation.
- Fundamental (structural) methods – These methods model the effects of economic and physical elements on electricity prices to describe price dynamics.
- Reduced-form models (quantitative and stochastic) – These models describe the statistical properties of electricity prices over time.
- Statistical approaches – These approaches use econometric models for power market calculations statistical forecasting techniques.
- Computational intelligence methods – These methods include machine learning and artificial intelligence based techniques that transform with complex dynamic systems.

To forecast day-ahead electricity prices, computational intelligence and statistical models have proven to show the best results [37]. Given the scope of this thesis, time series forecasting based on statistical modelling is used. Statistical modelling is easier to use and provides an easier visual interpretation of their components to engineers and system operators, but also has limitations, which are discussed in Chapter 7. Statistical models intend to do two main things- comprehend random processes within a time series and forecasting future time series [38].

Statistical modelling is achieved through five main methods [37]:

1. Similar-day and exponential smoothing methods –

    - Similar-day method clubs days with similar patterns, like similar weather condition, day of the week, particular holiday or consumption patterns, to forecast electricity prices for those kind of days [39]. As an alternative to using just a single day, a string of days can be used by using a linear combination or regression of various similar days. Upon trial and error, it was found that this method was not well calibrated and would not give accurate results [40].

    - Exponential smoothing method uses exponentially weighted average of historical observations to design price predictions. It is usually adopted in load forecasting, but its usage in electricity price forecasting has been seen in [37].

    $$\hat{x}_t = s_t = \alpha x_t + (1 - \alpha) s_{t-1} \tag{1}$$

    Every single smoothed value s_t in equation (1) is the weighted average of previous observation, where the value of parameter $\alpha \in (0,1)$ influences the weights (they decreases exponentially with the α value) [37]. Seasonal and trend components can be accommodated by expanding equation 28. Exponential smoothing is elaborately explained in a dedicated book [41].

2. Regression models –

    Regression models are the most commonly used statistical method. Multiple regression models denote the relationship between a dependant and independent variables (used towards prediction, also called predictor or explanatory variables).The relationship between variables is assumed to be linear in classical multiple regression (hence they fall under the category of linear regression).

The multiple regression model is shown in the form of equation (2).

$$y = \beta_\circ + \boxed{\beta_1 x_1 + \beta_2 x_2 + \cdots \beta_k x_k} + \varepsilon \quad (2)$$

As shown in equation (2, a multiple regression model is an extension of the simple regression model. The term that lies in the blue box refers to linear parameters, with $\beta_\circ$ referring to the intercept and β_k referring to the weights on x_k variables. ε is the error term. In a perfect multiple regression equation, the error term ε is assumed to be zero. In real life data, Estimated Multiple Regression equation is used (equation (3)).

$$\hat{y} = b_\circ + b_1 x_1 + b_2 x_2 + \cdots b_k x_k \quad (3)$$

As shown in equation (3), $b_o, b_1, b_2, \dots b_k$ are the estimates of $\beta_\circ$, $\beta_1, \beta_2, \dots \beta_k$ and $\hat{y}$ is the predicted value of the dependent variable. In multiple regression, an approximated change in y is observed by a one unit change in one of the explanatory variables, while holding other explanatory variables constant.

$$P_t = B_t X_t + \varepsilon_t = b_1 X_{t(1)} + b_2 X_{t(2)} + \cdots + b_k X_{t(k)} + \varepsilon_t \quad (4)$$

Equation (4) is used to represent linear regression, where B consists of coefficients in a 1 x k vector, X_t denotes a vector of regressors of dimension k x 1. The regressors are selected from explanatory variables that might have a correlation with electricity prices. This is considered to be a standard case.

3. AR type time series models –

A stochastic process consists of a set of random variables X_t, which may be dependent or independent variables, where t can take any integer value and refers to a moment in time. Time series is an implementation of a stochastic process.

Time series is affected by four main components. Time series decomposition, a statistical method based on rate of change in observed dataset, deconstructs a dataset into the four components mentioned below.

- Trend – This component reflects an overall change in the pattern of data for a persistent period, over a period of time. It also reflects the long-term regression of the series.
- Seasonality – This component represents a pattern of fluctuations (ups and downs) and not just a continuous increase or decrease. It reflects seasonality in the form of a specific pattern.
- Cyclicity – This component is seen if the duration between two cycles is much longer. It describes repeated but non-periodic fluctuations. For example, a cyclic pattern is seen when sales of clothes increase every December when there are discounts. This can be noticed when an industry goes through recession or economic growth as well. In cyclicity, the duration of time interval is not fixed, but it is for a longer period of time compared to seasonality.

- Irregularity – This component cannot be accounted for very easily, describing random and irregular influences. It represents the residuals in the time series after all other components have been removed.

Time series models that consider the time correlations and random nature of the events in focus, are called the Autoregressive Moving Average (ARMA) models. Time series forecasting is commonly used to forecast data recorded in certain intervals of time. Some frequently used methods are ARMA (p,q), autoregressive integrated moving average (ARIMA (p,d,q)) and ARIMA with exogenous variables (ARIMAX). These methods are based on the hypothesis that the datasets have features like Auto-Correlation, seasonality and trend [42].

ARMA model is a combination of AR and MA models, where AR denotes the autoregressive model of order p and MA denotes the moving average model of order q. To understand the AR term better, consider the example of a country's Gross Domestic Product (GDP). The GDP of the current year x_t can be dependent on certain factors like the population growth, setting up of new industries, GDP of the previous year x_{t-1} and can be presented as an AR(1) formulation, as shown in equation (5). AR(1) refers to the next instance being dependent only on the instance one unit before it i.e. t-1 instance. α is a coefficient that is used to minimize the error function, ε_t. Since every x_t is dependent on x_{t-1} and every x_{t-1} is dependent on x_{t-2} and so on, any shock to x_t will only produce gradual effects in future. This can be visualized as a gradually dropping or gradually increasing exponential curve.

$$x_t = \alpha * x_{t-1} + \varepsilon_t \qquad (5)$$

To understand the MA term better, consider the example of a local ice cream shop, situated next to a commercial big ice cream chain. The sale of ice creams was zero for many days, until the owner of the shop decided to experiment and come up with a new flavour that was not available in any ice cream shop in the town in which it was located. Hence the entire batch of ice cream, say x_t made was sold. As a result, there were around 10% of the people who were not able to buy this ice cream, creating a gap denoted by the error term. This can be visualized as a quickly dropping exponential curve.

A major difference between an AR and a MA model is how quickly the model is affected when exposed to shock. This is based on the correlation between different time series objects at different points in time [43]. In an MA model where n is greater than the MA model's order, the covariance between x_t and x_{t-n} is zero. Covariance is a measure of the relationship between two random variables. In the AR model, when the n gets larger, the correlation of x_t and x_{t-n} slowly declines.

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \qquad (6)$$

$$X_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \qquad (7)$$

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \qquad (8)$$

Lag is a term that is often used in ARMA models. Lag is basically a time delay. Lag-1 refers to a shift in time series by 1 before comparing the time series with itself. A perfect correlation is found at Lag-0 since the same values are being compared with each other without any shift. If the time series consists of random values, a correlation will be seen at Lag-0 and nowhere elsewhere. For example, in the aforementioned GDP example, lag refers to the time at point x_{t-1}, x_{t-2} and so on. But in the ice cream example, finding a correlation at different lags will be next to impossible, due to the gradual decline in sales.

The equations (6), (7) and (8) translate the theory presented on MA and AR until now in terms of electricity prices. X_t represents the current whose current value is denoted in terms of p lagged values (autoregressive) and in terms of q preceding values of the ε_t , white noise term (moving average) [44]. For instance, in an AR model, X_{t-1} would be the first lagged term, X_{t-2} would be the second lagged term and so on. $\varphi_1 \ldots \varphi_p$ and $\theta_1 \ldots \theta_q$ are parameters of the models and μ is the expectation of X_t (usually taken to be 0). An AR(p) and MA(q) model are denoted in equation (6) and (7) respectively [44] and the entire ARMA model is shown in equation (8).

The knowledge of p and q are essential for any ARMA based model. One of the ways to find the right order of p and q, is to use Total Correlation Chart (also known as Auto Correlation Function [43]). Auto correlation function (ACF) is a plot of correlation between the different lag functions i.e. the correlation of x_t at x_{t-1} or x_{t-2}, and so on. Just as how a correlation displays how related two time two series are, Auto-Correlation displays how related the time series is with itself. ACF and PACF are methods to form relations between current and past series values and gives a sense of what previous values are most beneficial in predicting future values. ACF is a statistical measure that signifies how a time series is related to itself and its lagged values over time. Given a lag k, this function gives a correlation between values of a series that are k intervals apart. In a MA series with lag k, finding a correlation between x_t and $x_{t-(k-1)}$ is not theoretically possible due to the sudden effect on this MA model when subjected to a shock. The total correlation chart dies at the k^{th} lag [43]. ACF can be used to find an estimate of q and partial Auto-Correlation function to find an estimate of p.

In ARMA modelling, data is assumed to be weakly stationary and if not, it is transformed into stationary data. This is extremely important in a time series like electricity prices as these prices are never stationary. The easiest way to do this is by differencing. A general model introduced by Box and Jenkins [45] consisted of both AR and MA parts, combining differencing in the formula. Once differenced, a “d” element is introduced into the ARMA model and the resulting model is the ARIMA(p,d,q) model. Differencing is a technique achieved by subtracting prior values from the current values. If the series is still not stationary, then another level of differencing is done with the first level differenced series.

At times, repeated differencing at Lag-1 is not sufficient to make the series stationary. For datasets with multiple seasonality, like energy consumption and electricity prices, differencing at longer lags is essential [37]. Such processes are carried by seasonal ARIMA (SARIMA) models. SARIMA is represented by ARIMA(p,d,q) x $(P,D,Q)_s$, where (p,d,q) denotes the order of non-seasonal part and $(P,D,Q)_s$ that of the seasonal part, the subscript ‘s’ standing for number of points in the seasonal pattern.

Modelling electricity prices becomes difficult due to the multiple seasonality that these datasets possess like daily, weekly and annual seasonality, and also due to the random spikes or price jumps in the data. A simple ARIMA model is not compatible with seasonal data, it assumes the data to either be not seasonal

or the seasonal component is removed. Statistical modelling usually combines historical electricity prices with other exogenous variables like weather or consumption patterns to forecast electricity prices. There exists extensive literature that try to shortlist the most significant factors that will provide an accurate forecast, but no such standard has been found yet as each electricity market of a country behaves differently.
Now that the important keywords that is going to be used for time series modelling and forecasting has been explained, this report now moved forward with both the processes. It should be noted that both processes have been carried out purely in R-programming software.

As seen above, some techniques are rather simple than others to forecast future time series data. Regardless of which method is utilized to produce quantitative forecasts, the first move is to visualize the data i.e. historical data. This is an important part of pre-processing the data and has been carried out below, as shown in Figure 7.

Step 1: Cleaning and processing of data

Before beginning modelling with the dataset, it is essential to clean and process the data. This makes the data smoother to work with. Regarding electricity prices, this implies removing outliers using various techniques. There are several methods for dealing with outliers in electricity prices in [46], but there is no agreement on standard threshold value of electricity prices, which if surpassed, is considered an outlier. As per [46], some of the techniques mentioned for outlier detection are:

- Fixed Price Threshold – If the electricity price surpasses a certain price, then it is considered an outlier
- Variable Price Threshold – A percentage of maximal and minimal values are considered to be outliers
- Fixed Price Change Threshold – A value that denotes a change in price, exceeding a fixed value, is considered an outlier
- Variable Price Change Threshold – If the price surpasses a value that is three times the standard deviation, it is considered an outlier.

In this report, R-programming was used to directly clean the outliers in the dataset using function `tsclean()` of package `{forecast}`. Other packages that deal with outliers are `{extremevalues}`, `{outliers}` etc. `tsclean()` identifies and substitutes outliers with the help of techniques involving series smoothing and decomposition.

Smoothing enables the trend in time series to be observed clearly by smoothing out the irregularities to a certain extent. In the Figure 6, the hourly data of 2014-2018 has been smoothed using ordinary moving averages that calculate the averages of observed values at each time preceding a specific time. Daily MA calculates the moving average of the past 24 hours of data in each day, monthly MA takes into account past (24*30) values, weekly MA takes into account past (24*7) values and yearly MA past (24*365) values to create different smooth curves, where all of the periods taken into account signify seasonal periods.

Step 2: Decomposition of data into trend, seasonality, irregularity

Historical data usually has sources of variation and the simplification of these patterns can result in more precise forecasts. The trend, seasonality and irregularity (i.e. randomness) is observed when data is decomposed, as shown in Figure 9. As seen from Figure 6, there was an increasing trend from the midway of the 3rd year (2016) onwards and no repeating trends. The same can be seen from the moving average smoothing curves as well, shown in Figure 6. This proves that the data was decomposed correctly taking into account multiple seasonality factors in R.

Step 3: Stationarity of data using ADF test

After the decomposition, stationarity of the time series is confirmed. This can be carried out by either visually observing the ACF and PACF plot or by carrying out the ADF test. Augmented Dickey-Fuller (ADF) is the most commonly used test for testing stationarity. The ADF test is carried out using a simple function `adf.test(y, alternative="stationary"`. It is based on the hypothesis that the data is non-stationary and it checks if an alternative hypothesis of the data being stationary is true. The data was adjusted to fit stationarity by also adjusting the “d” values.

Step 4: Choosing the correct ARIMA model order (ACF, PACF plots or auto.arima() results)

To choose the correct ARIMA model order, again ACF and PACF plots were observed. After seeing at what lag the ACF and PACF plot cuts off, the value of q and p can be decided. ACF and PACF plots measure the relation between past and present series values and suggest which previous values are the most beneficial in predicting the future value. Another way is by utilizing the `auto.arima()` function. It iterates several times until it is able to find an optimal model and an efficient (p,d,q) order.

The `auto.arima()` function returns the best fitting ARIMA model based on Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) values, of a univariate time series. Both AIC and BIC are measures of the quality of a predictor model [41]. For a good fitting model, both AIC and BIC values are supposed to be as low as possible and the choice of the information criterion can be given in `ic = c("aicc", "aic", "bic")` in the function usage shown below. It gives a “d” value based on both first-differencing as well as seasonal-differencing as well as their maximum values. It gives the maximum values of p and q as well. It does not restrict the fitting of the model to stationary, upon specifying if `stationary = TRUE`. By changing the `stationary = TRUE`, it fits the model according to seasonal models. Once the best-fitted model is found, this model is then used to forecast future values using a very simple `forecast()` R-function.

The historical data used for visualization consists of hourly points from 2014 to 2018. A simple univariate forecast, with the help of the `auto.arima()` function in R-programming, is used in this study to predict the hourly prices of the next 25 years, from 2019 to 2043. The scope of this thesis was not to focus completely on data analytics. Data analytics was merely a tool to address the main research question. There is a vast potential for making this forecast more accurate by using more complicated ARMA models like Seasonal ARIMA models that combine various exogenous variables. This point has been discussed in detail in Chapter 8.

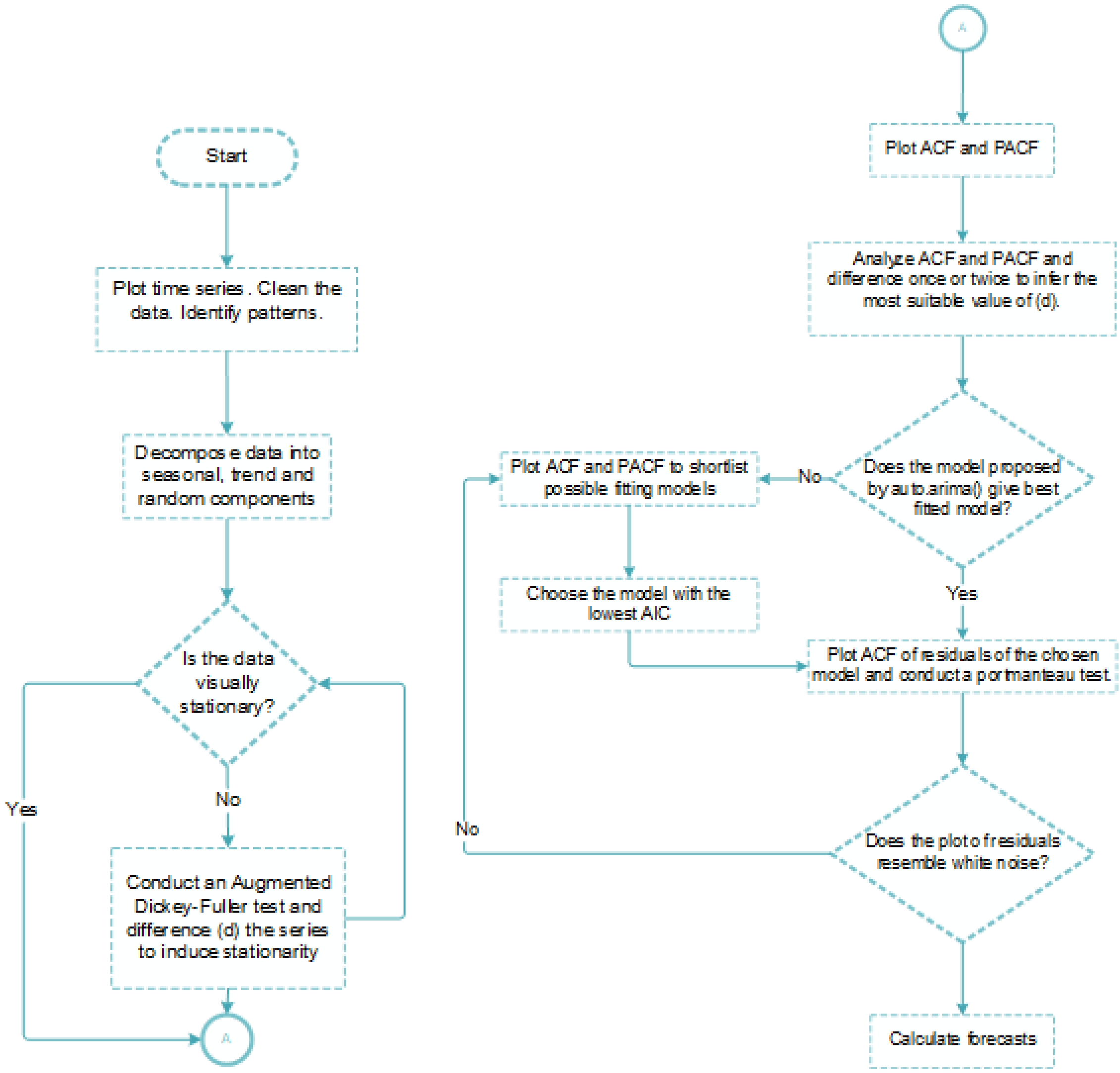

Figure 7: Hourly electricity price modelling

In order to validate if the forecasted price follows the correct trend, hourly prices for 2017 and 2018 were predicted using the historical trend noticed in the hourly prices between 2014 and 2016. Upon the superimposition of the forecasted day-ahead price on the actual day-ahead price (since this data was available from the ENTSO-E platform), it is concluded that the hourly forecast of 2017 and 2018 was very close to the actual values, thus moving forward with the 25-year hourly price forecast, as shown in Figure 8. Apart from superimposition, the goodness of fit was also quantified by using root mean square error (RMSE) and mean absolute error (MAE) values. MAE calculates the mean of the magnitude of errors in the forecasts, calculating the accuracy of the variables forecasted. RMSE measures exactly what it stands for – difference between actual and forecasted values is first found and then this value is squares and averaged over the sample size. The square root of the result is then used. RMSE is used when a forecast with the least amount of large errors is required. The RMSE is constantly larger than MAE, but a good fitted model makes sure that the RMSE is not too large, as that would mean that errors are of different magnitude. There is no one benchmark error value for either RMSE or MAE in electricity price forecasting [37] [47]. Hence, the error metrics were compared to another study that used a similar model to forecast prices, where an entire year's day-ahead price were forecasted using the historical prices of the previous year, giving a

RMSE of 15.9% and MAE of 11.6% [44]. The data forecasted in this study had a RMSE of 18.1% and MAE of 13.9%. These values were assumed to be comparable and the fit was assumed to be good. It should be noted that all the error metrics were found using functions in R.

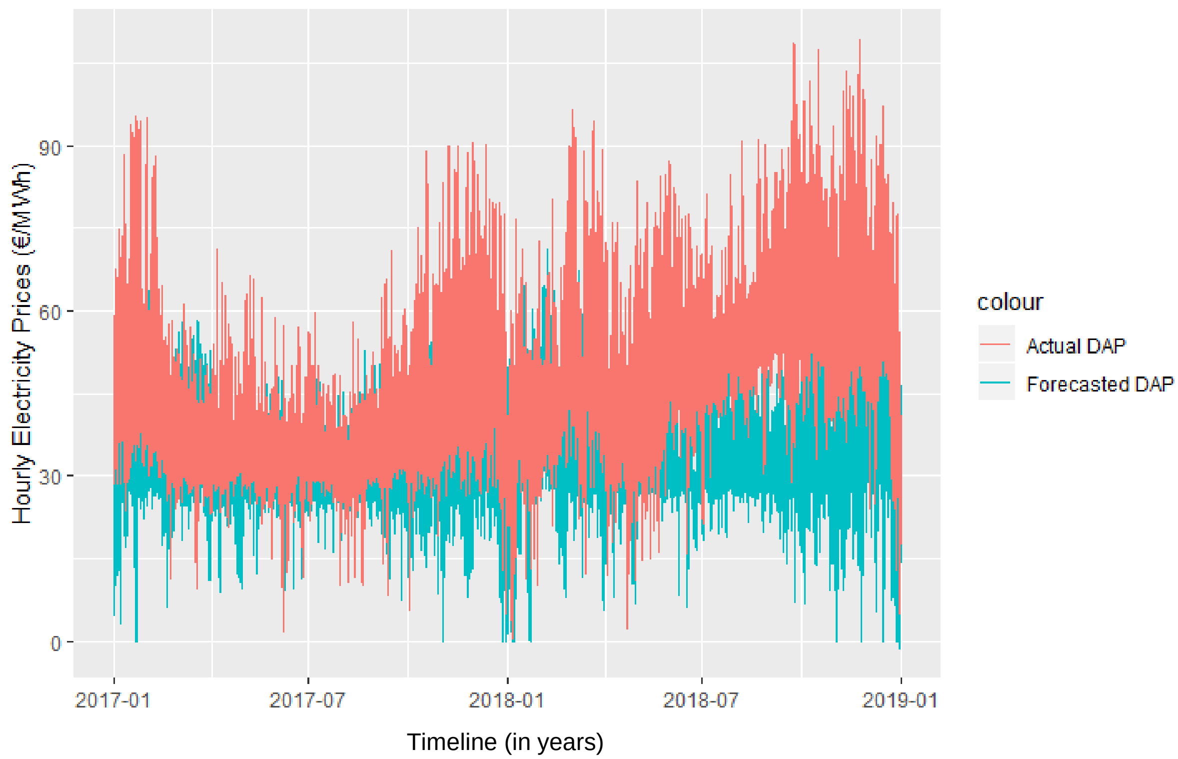

Figure 8: Superimposition of Training set (Actual Day-ahead Prices) and Validation set (Forecasted Day-ahead Prices)

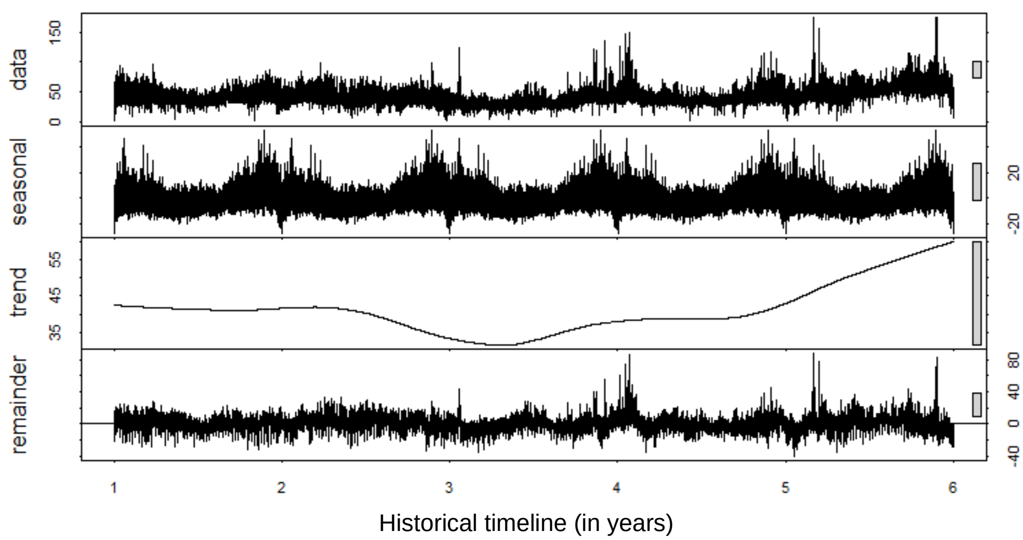

Figure 9: Decomposed hourly electricity prices 2014-2018

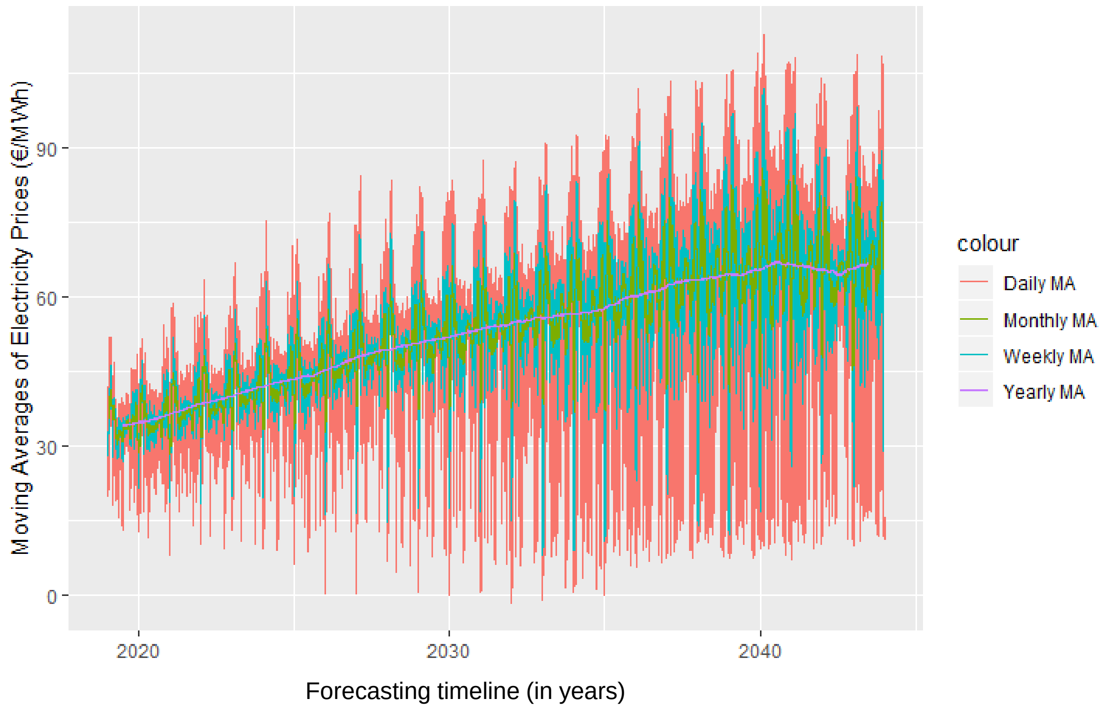

Figure 10: Forecasted trend (as MA- moving average) in electricity prices (2019-2043)

3.3 Evaluation of electricity price volatility

Electricity price volatility can be measured and represented in several ways. [48] portrays volatility using the SARMA (seasonal autoregressive moving average) model. It enabled the authors to develop price volatility forecasts belonging to historical data from previous days and consumption patterns. [6] uses the GARCH model (generalized autoregressive conditional heteroscedasticity) to represent price volatility. In an attempt to use a simplified method to calculate electricity price volatility, the method in [35] was adopted. [35] uses the standard deviation equation to calculate the price volatility, v_d for a day, d.

$$v_d = \sqrt{\frac{1}{24}\sum_{h=1}^{24}(p_h - p_d)^2} \tag{9}$$

In equation (9), p_h stands for hourly prices (€/MWh) and p_d stands for average daily price (€/MWh). If the weekly volatility had to be found, the parameters used in equation (11) will be used.

$$p_d = \frac{1}{24}\sum_{h=1}^{24} p_h \tag{10}$$

$$p_w = \frac{1}{7}\sum_{d=1}^{7} p_d \tag{11}$$

In order to use equations (9), (10, (11, the future hourly forecasts are used. The results of daily electricity price volatility are displayed in Figure 11. It is seen that like the average electricity prices, even the electricity price volatility has an upward trend. The electricity prices develop extreme volatility with a range of approximately €5 to €200 per MWh. To understand what factors affect this significant increase in the volatility, a regression analysis to find the relationship between certain factors and price is carried out in the next section.

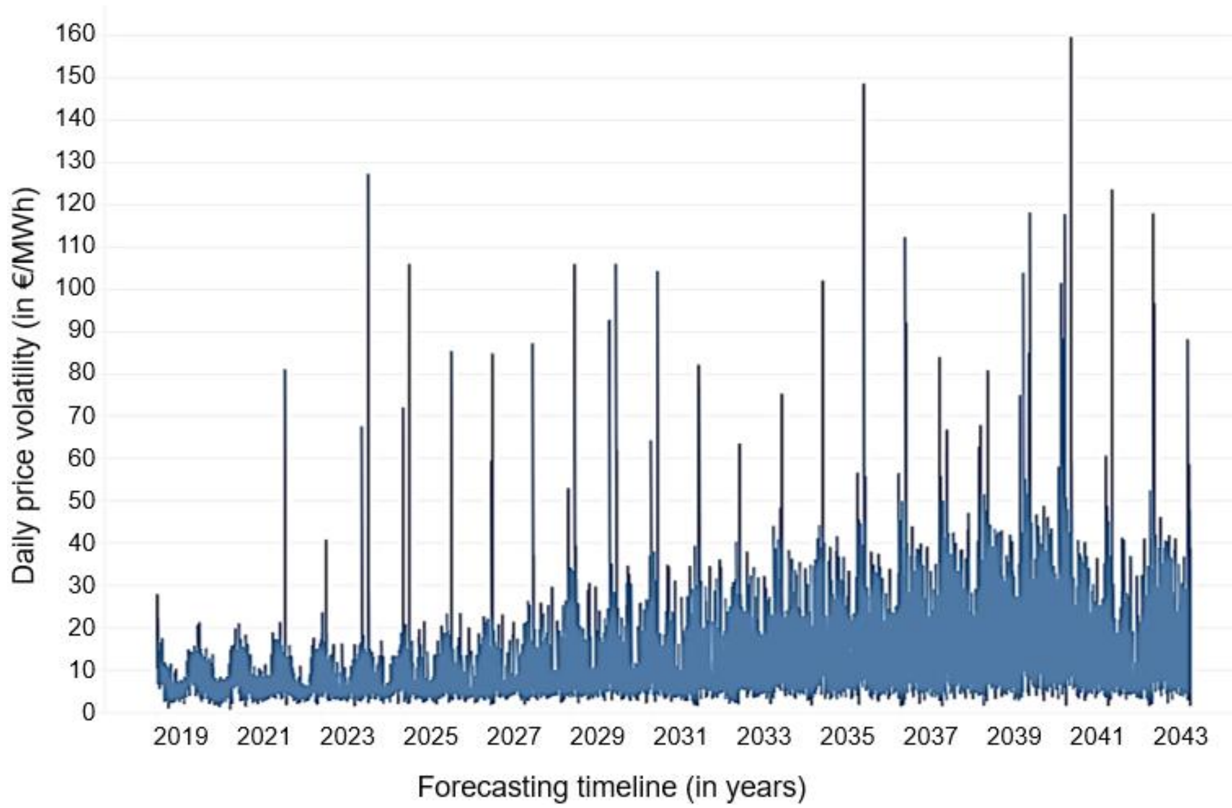

Figure 11: Daily volatility of electricity prices (€/MWh)

3.4 Factors affecting electricity price volatility

Statistical approaches can prove to be a very useful tool in answering questions like: How associated is variable X representing either the demand, RES penetration into the grid etc., to variable Y representing the electricity price? What can be the relationship between these two variables? Can we use this relationship to predict electricity prices?

Correlation is often considered to be the go-to tool to describe statistical relationship, however correlation only estimates the strength of the relationship of two variables i.e. if there is a significant association or not, and does not quantify it further. To model the association between magnitude of one variable (say, demand) and that of the second (say, price), simple linear regression can be used. Regression helps to quantify the nature of this association, while Correlation shows the strength of this association. Hence Regression will be used to understand the relationships and create various scenarios for sensitivity analysis.

The fundamental idea behind the regression equation is denoted in equation (12.

$$Y = b_o + b_1 X \tag{12}$$

Y can be referred to as the target, response or dependent variable and X can be referred to as the feature vector, predictor or independent variable. A simple linear regression models the degree of change in Y when X changes. For the quickest analysis and to get an idea of the overall trend, the change in price (Y) can be predicted from various parameters (X) using a linear relationship with each of this factors. This analysis is useful when the base case is preserved and each parameter is changed to a certain amount. It is worthy to note that the relationship might not always be linear, but since this thesis does not intend to go into the depths of data analytics and is focussed more towards providing an overall sense of the data, linear regression is a good enough tool. For example, in [49], linear regression was used to estimate the relationship between extremely noisy and non-linear time series data, across various disciplines ranging from physiology to biogeochemistry.

Using the linear model function in R, the intercept (b_o in equation (13) is found to be 39.802182 and can be understood as the predicted Price for solar penetration of 0MW. The regression coefficient (b_1 in equation (13) is found to be 0.005145 and can be understood as the following: for every extra MW of solar penetration, the electricity price is increased by 0.005145. This data will fall exactly on the straight line that linear regression stands for. However, in reality, data does not always fall on this line, in which case the regression equation must include an error term, ε_i.

$$Y_i = b_o + b_1 X_i + \varepsilon_i \tag{13}$$

Regression analysis also gives the fitted values (denoted by $\hat{Y}_i$) and residuals ($\hat{e}_i$). The hat on top of the letters represent the fact that these values are estimated and not known.

$$\hat{e}_i = Y_i - \hat{Y}_i \tag{14}$$

The regression line is based on an estimate after minimizing the sum of squared residual values, known as residual sum of squares (RSS). Least squares regression is the technique used to minimize the RSS. The goal of regression is to highlight the linear association between the target (electricity prices) and predictor variables. This is done by understanding the connection between both variables and describe it using the data that the regression was made to adjust to i.e. the main emphasis is on the estimated slope value .

Since in the case of the electricity price model, multiple parameters are used to predict the value of price, the linear regression can be simply extended to multiple regression, where each parameter has individual linear relationships and other concepts like fitting using least squares method also holds true. It can be represented by the following equation (15, and the coefficients can be interpreted the same way as in linear regression. The variable to be predicted, Price $\hat{Y}_i$, alters by the value of coefficient $\hat{b}_1$ for each unit change in $X_{i,1}$.

$$\hat{Y}_i = \hat{b}_o + \hat{b}_1 X_{i,1} + \hat{b}_2 X_{i,2} + \cdots + \hat{b}_p X_{p,i} \tag{15}$$

To evaluate the overall accuracy of the multiple regression model, Root Mean Squared Error (RMSE) is used to compare an existing model with others. It is the square root of the mean squared of the error in the predicted values and is found using a function in R i.e. using `summary (model)`

Table 1: Correlation matrix based on some factors affecting the electricity prices

	Intercept	Solar Penetration	Offshore Penetration	Onshore Penetration	Load
Coefficients	2.6714991	0.0001758	0.0431611	-0.0091126	0.0031066

Table 2: Error values in the correlation matrix of some factors affecting the electricity prices

	Estimate	Standard Error	t value
Intercept	2.6714991	0.3294	8.109
Solar Penetration	0.0001758	0.0001711	1.027
Offshore Penetration	0.0431611	0.0006388	67.570
Onshore Penetration	-0.0091126	0.0001311	-69.523
Load	0.0031066	0.00002641	117.635

To theoretically understand the data in the above tables, an extra MW of solar penetration into the grid increases the estimated value of the price by roughly a factor of €2.6715 and adding around 10 MW into the grid can increase this factor by €26.715.

The t- value stands for the extent to which a coefficient is statistically significant. Higher the value of "t", the more significant is the predictor. This helps to choose which variables to include as a predictor. From Table 1 and Table 2 above, it is clear that including onshore penetration is the least statistically significant. The fact that Load has the highest value also aligns with the rest of the literature published.

Upon analysing the correlation coefficients in Table 1 and Table 2, it is evident that a higher availability of offshore wind in the generation mix affects the electricity price more heavily than other factors. This has a direct effect on the electricity price volatility. When wind is available in plenty, the growing demand can be met with wind, but the unpredictable nature of this RES also forces expensive power plants to meet these needs in the event that wind becomes unavailable. [50] states that an increase in carbon emission prices will also have an adverse effect on electricity price volatility.

4 The Hedging Strategy

With higher electricity price volatility in a renewable energy-rich electricity market, there is definitely a need to make the existing hedging mechanisms, implemented via traditional contracts, more dynamic and responsive to uncertain changes in supply and demand. Hence, there is a massive potential to modernize existing hedging techniques. This chapter aims at designing a hedging strategy that monetizes the electricity price volatility using a physical tool (BESS, in the case of this thesis). The hedging strategy is carried out using energy arbitrage, as mentioned in chapter 1.

4.1 Essential factors driving the proposed hedging strategy

Electricity prices in the day-ahead market are predicted to only get more volatile, as seen in Figure 11. These fluctuations in prices have the possibility to expose generators, suppliers and consumers to substantial risks. If there are two stakeholders involved, electricity price volatility can prove to be an attractive business case for one but loss incurring for the other. For example, the suppliers provide electricity to the end-consumers for a certain price as per a certain contractual agreement. The suppliers in this case have the obligation to supply electricity no matter what, thus being exposed to the risk of sudden spike in wholesale prices, while also being in a position to forego a drop in wholesale prices.

Hedging allows both the parties involved in a transaction to avoid bearing the risk. A high price that may be a bad outcome for one party may be a good outcome for the other, if they agree to a hedging technique. There is no standard definition of hedging. **In this study, hedging will be defined as "a valid strategy made to minimize or transfer risk in order to protect the entity from future unpredictability rooted from electricity price".**

The fundamental idea behind the hedging strategy proposed in this thesis is arbitrage. Arbitrage indicates a mechanism via which profits can be incurred by buying and selling multiple equivalent commodities while minimizing risk [51]. Arbitrage is usually utilized for purchasing a relatively low priced commodity and selling it when it becomes over priced, for profit. Restructuring of the power industry has resulted in frequent disparities in electricity prices, that provides to be potential for arbitrage. This section introduces arbitrage from a broad perspective and then examines potential of arbitrage in power markets. To understand the principle underlying arbitrage, it is essential to know that arbitrage is driven by three factors: objective, opportunity and means [51]. In the electricity market, objective of arbitrage is making profit from price volatility, by monetizing on periods where electricity price hits abnormal peaks and troughs.

The induction of RES into the grid is known to bring about such indiscrepencies in the prices. Hence the opportunity for arbitrage is due to these price spikes.

The private entity that uses the hedging strategy will be referred to as an arbitrageur i.e. an organization that carries out arbitrage. From the stand point of this thesis, this arbitrageur will use a BESS as means to arbitrage, hence indulging in hedging using. An advantage of using BESS to carry out arbitrage is that simultaneity does not have to be satisfied, like in other aspects of the electricity network where demand and supply have to be balanced at all times.

In this study, being in a deregulated electricity market, the arbitrageur relies upon day-ahead electricity market price than on the load to make decisions to be taken in the long run and in the short term.

Importance of short-term and long-term electricity price forecasting in designing the hedging strategy

Modelling electricity prices cannot be carried out in the same way as modelling in any other commodity or financial market, due to a lack of cost-effective way to store electricity and the need to maintain a demand and supply balance at all times. Estimating how the electricity prices are distributed is beneficial in the prediction of short-term market behaviour, which can be helpful to the power suppliers and service providers in monetizing on the volatility in the electricity market [52]. It can also prove to be useful for new entrants in the electricity market or investors to make significant decisions about long-term budgets based on probabilities, backed with the other facts, and about the relative investment [52]. Short-term electricity price forecasting is gaining more popularity with an increase in variable renewable energy production in the grid. Unpredictable electricity generation has exposed the market participants to higher risk from variations in electricity prices, but this volatility in market prices can be converted into monetary gains. Utility companies will be forced to make decisions under uncertainty. Higher the knowledge the participants possess on the probability distribution of process, the higher are chances for them to face less risks in a competitive market [53]. A reliable short-term electricity price forecasting increases the quality of decision-making in areas like risk management, to assess the potential for providing energy from certain units or to decide the supply bid function through the use of stochastic bidding and dispatch models [54]. Forecasting hourly data is also useful to make long-term decisions like to carry out a realistic valuation of flexible assets, to design stochastic optimization models or to forecast profitability.

Short-term forecasting alone cannot drive the design of the proposed hedging strategy. Long-term forecasts will allow the private entity or arbitrageur to gauge whether investing in a storage technology at a certain level in the distribution grid will be economically feasible, helping it short-list the nature of the BESS to invest in. Long-term forecasts have already been carried out and analyzed in the previous chapters and it is assumed that the arbitrageur that implements this strategy will carry out short-term forecasts as it gets closer to the day of implementing the strategy.

Motivation behind using probability density functions to design the hedging strategy

This study aims at using an analytical approach to design the hedging strategy using storage units. An analytical approach makes use of a suitable process to break down the problem statement into smaller pieces, that then become easier to solve. Studying the probability density functions and distribution of electricity prices provides market participants (suppliers and buyers) to manage the selling and buying of resources and also helps the regulatory authority to monitor intervals that deviate from normal distribution. Several areas in the electricity market use probability distributions of electricity prices, for example for electricity price forecasting, evaluation of market risks, bidding strategies and power flow strategies [52].

Different researchers assume different probability distributions to explain the electricity prices, the most common one being normal distribution. In [55], the authors take electricity price during each time interval of one hour to obey a normal distribution concerning unit commitment issues of single power supplier. The authors in [56] assume hourly electricity prices related to fuel prices of electricity generation to follow normal distribution, while designing the risk management structure of power supplier and while investigating bidding strategies [57]. Other distributions like triangular, stable, subbotin and beta distribution have also been reviewed by researchers. However it is worthy to note that the papers that consider non-normal distributions take the entire dataset while fitting the hourly prices to a fitting probability distribution function. This study stochastically considers 24 points of several days and shows that the hourly price data of a day fits a normal distribution. It should be noted that no matter how accurate a future forecast is, the future can never be accurately predicted. So there is a chance that the prices of a day may not follow normal distribution and may follow some other probability distribution function. However, in the event that the hourly prices follow a normal distribution, this strategy can be very efficiently applied.

4.2 Designing the hedging strategy

The basis of designing this hedging strategy is to see if the data can first be portrayed as a normal distribution. This is done in the following two steps:

Step 1: Verify if the probability distribution function of the entire population is Gaussian

Backed by the aforementioned literature reviews that carry out their study based on the assumption that the hourly electricity prices can be normally distributed, this work considers the hourly electricity price of a day, which is the market clearing price set every hour, to be a Gaussian distribution [58]. To check how far this is true in the dataset that was forecasted for the years 2019-2043, a histogram of the electricity prices is plotted in It can be seen that even over 25 years, the prices follow a normal distribution.

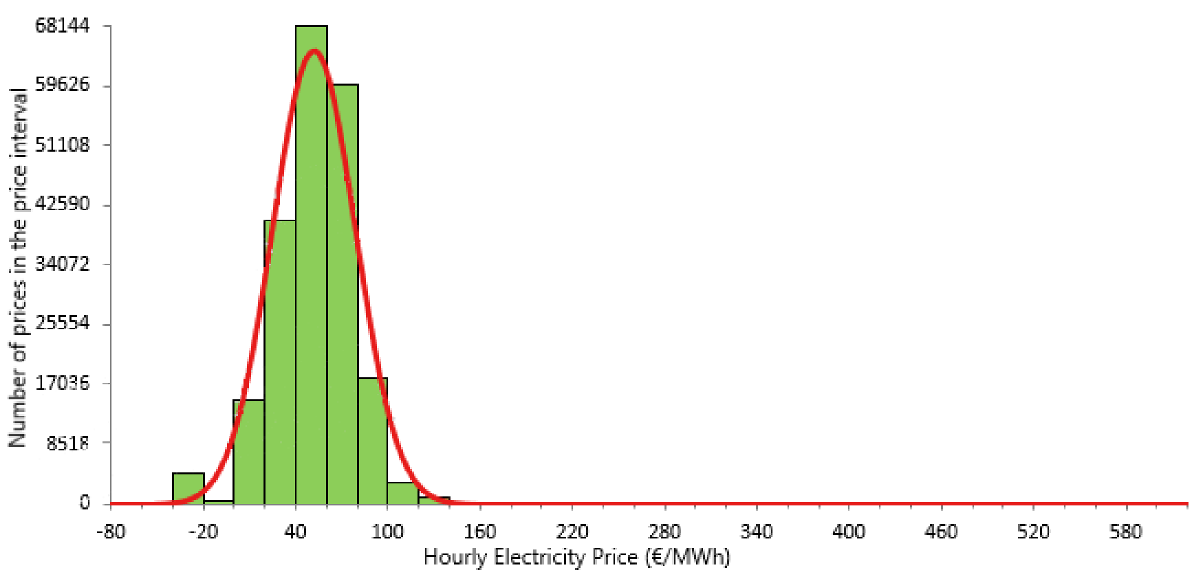

Figure 12: Depicting hourly electricity price (2019-2043) in a normal distribution

Step 2: Verify if the probability distribution function of hour-wise daily sample is Gaussian

The electricity price distribution over 24 points of four random days are considered in the Figure 13 below. A Quantile-Quantile (Q-Q) plot is a visual statistical tool used to see if these randomly chosen days consisting of 24 data points follow a normal distribution (Figure 13). The "quantiles" on the y axis refer to percentiles i.e. the points below which a specific part of the data falls; it refers to a percentage of falling below a certain value. The "theoretical quantile", refer to the quantiles from the in-built normal distribution this algorithm uses as a standard, with mean 0 and a standard deviation 3. It is found that these are fairly normally distributed, as most of the points either fall on the 45 degree line or very close to it. This 45 degree line is a reference line and any distance-specific departure from this line, shows the departure from it following a normal distribution.

Further, to test statistical significance of the results from the Q-Q plot, various hypothesis tests, like Shapiro-Wilk and Anderson-Darling can be conducted. These tests test for specific patterns of non-normality. Anderson-Darling test is used to test specific distributions, whereas Shapiro-Wilk can be used to test the normality of any distribution with a mean and variance and is considered more powerful for a sample size between 3 and 2000 [59]. Shapiro-Wilk tests the normality in frequent statistics by proving a hypothesis null or alternative. The hypothesis is that the sample selected at random follows a normal distribution and is supported using W-statistic and p-value as evidence, that are yielded as a result of the Shapiro-Wilk test.

There is no universal standard against which both W-statistic and the p value can be compared against. If the W-statistic is extremely small, then the distribution is not considered a normal distribution. The p value points to whether the hypothesis was statistically significant. If the p value falls below the chosen alpha level, then the results point towards being statistically significant. Alpha is usually chosen differently by different statisticians, but the most commonly used significance level is 0.05, which refers to 5% chance that the result occurred at random [60]. If the p value is less than 0.05, the null hypothesis is rejected. It shows that there is enough evidence to say that the population is not normally distributed. If the p value is greater than 0.05, then the null hypothesis fails to be rejected, which means there is enough evidence for the sample to be normally distributed. In the cases that are chosen at random (displayed in *Table 3: Numerical test values for normal distribution*Table 3), it can be inferred that the samples chosen are normally distributed.

Table 3: Numerical test values for normal distribution

	W-statistic	p-value
01.02.2019	0,91	0,4352
02.08.2019	0,95	0,2295
01.02.2022	0,93	0,1206
02.08.2022	0,91	0,2111
01.02.2025	0,94	0,3968
02.08.2025	0,95	0,2147
01.02.2030	0,96	0,3322
02.08.2030	0,91	0,4924

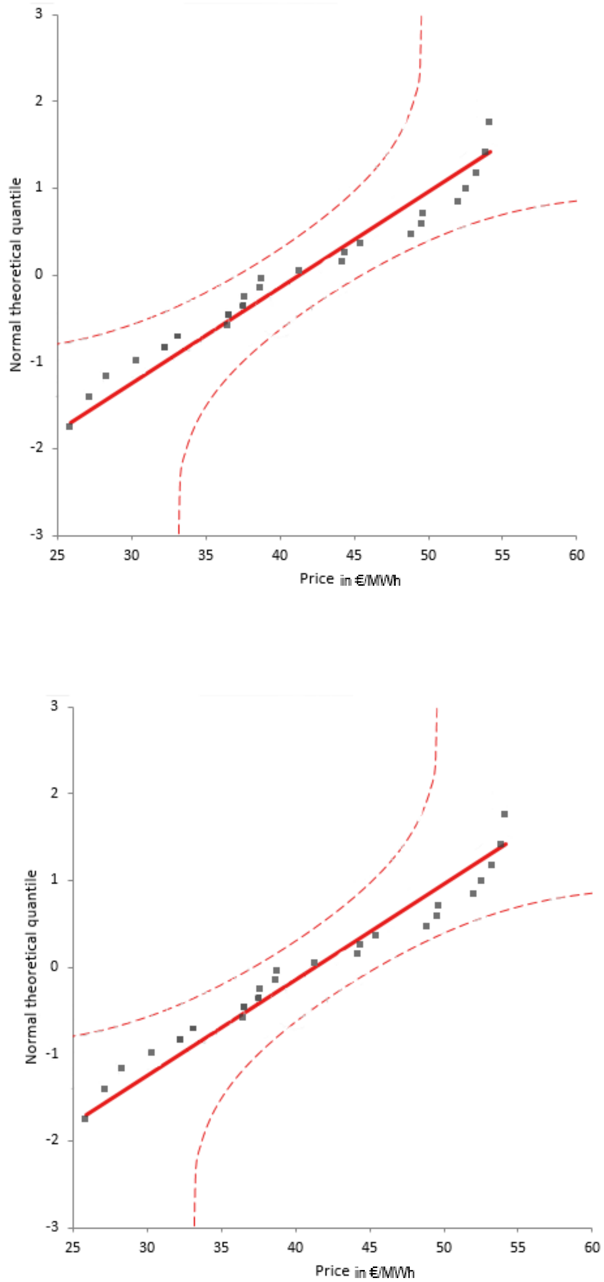

Figure 13: Choosing four random days for Q-Q plot representation; Top left – 01.02.19; Top Right – 01.08.19; Bottom Left – 01.02.30; Bottom Right – 01.08.30

4.3 Reasons behind choosing a normal distribution

Many reasons formed the driver for choosing normal distribution as the stepping stone to designing the hedging strategy of this study. One reason was the versatile and well-studied nature of the normal distribution. Normal distribution plays a significant role in statistical thinking and modelling [61]. If the distribution was noticeably non-normal, the conclusions drawn from it have been found to have a probability of being wrong [61], despite being able to calculate various test statistics based on it. Normal distribution statistics are very efficient and several studies have advised to normalize transformations to be able to use conventional statistical methods like the normal distribution [61]. Normal distribution forms the basis for many probability distributions, thus showing a strong property of analytical reformulation. It is known that the cumulative function of any dataset will form a normal distribution [61]. For example, the Poisson distribution tends to a normal distribution as the rate parameter (which lies on the y-axis) increases. Poisson distribution is an extreme form of binomial distribution, which also has a tendency to tend to a normal distribution when the number of trials (lying on the y-axis) increases.

Another reason why normal distribution curve was used to design a strategy for hedging was its ability to measure uncertainty. To evaluate the uncertainty included in a probability distribution $f(x)dx$, the fundamental way to approach this is to use the entropy function, given by the (16 [62].

$$\mathrm{H(f)} := -\int \mathrm{f(x)} \log \mathrm{f(x)dx} \tag{16}$$

It was found that out of all distributions with a mean and variance, the Gaussian distribution was able to maximize the entropy function the most [62]. Since this study deals with trying to reduce the exposure to volatility, which is a form of uncertainty, it was deemed best to begin conceptualizing the strategy first based on the normal distribution.

The fact that the Gaussian distribution gives an accurate estimate of the proportion of area under the curve around the mean and between mean and standard deviation in a step of 1 unit, in the form of the empirical rule, was the key factor behind opting to design a strategy using this distribution. The empirical rule, also known as the 68-95-99.7 rule, describes the percentage of values that fall within a bandwidth around the mean, where 68.27% of the values will lie within one standard deviation of the mean and 95.45% will lie within two and 99.73% will lie within three standard deviations.

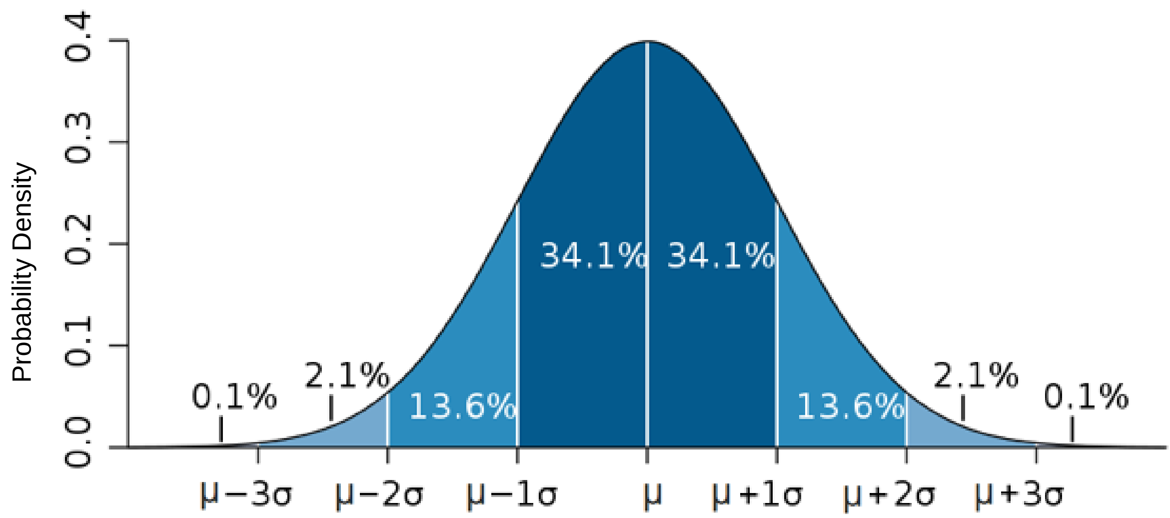

Figure 14 – Empirical formula in a normal distribution

Other probability distributions can also be used to represent hourly electricity prices of each day. The Student-t distribution, another variation of normal distribution, was proposed as an alternative to the normal distribution as it is shaped taller in the middle of the plot and has the ability to incorporate fat tails [63]. In the event that electricity prices show fat tails, the data can also be described by α-stable distributions [47]. By showing that using a normal distribution, this strategy is economically feasible, it can be used with more complex distributions in the future. The statistical complexity is not within the scope of this thesis and the methodological scientific contribution is the method of designing the strategy.

4.4 Implementation of the hedging strategy

Renewables have a very low marginal cost and usually lie at the bottom of the merit order. Marginal cost ($\frac{dP}{dQ}$) refers to the price (say, P) required to produce one additional unit of electricity (say, Q). For generators, this cost is heavily influenced by the fuel cost, while other variable costs like maintenance costs have a small impact. Lack of fuel consumption, lesser operating costs and presence of government policy incentives allows renewable energy generators to bid into the market at very low, zero or even negative prices, forcing the wholesale electricity prices to go down. The method by which the market price is set is called the **merit order effect**. The merit order determines the order in which power plants participate in the market, with the starting point set by the least expensive price offered by the generator with the least running costs. The presence of renewables in the electricity markets pushes the expensive power plants down the order (usually owned by municipal authorities and large utilities) and the ability of solar peaking during the day time when the peak demand is high, making them more vulnerable, setting a lower starting price.

Nuclear also has a low running cost and is placed either at the same level or a little above renewables in the ranking. If the carbon permits are lowly priced, then the cost to run a coal plant become typically lower than that of a combined cycle gas plant (CCGT) and CCGT goes above in the merit order. Peaking plants which are installed to manage the sudden peak in demand are usually diesel or expensive gas turbines and are often placed at the end of the merit order due to their expensive running costs. The market operator aggregates the generation bids offered by these plant owners to form a supply curve, along with aggregating the demand bids to form a demand curve. The market clearing price is set at the intersection of these two curves and is locked hourly and will be dependent on the technologies that set it [64]. Since renewable energy generators are price-takers, they set the price. Hence, it is safe to say that **the leftmost prices that are away from the mean represent the prices set by RES penetration and the rightmost prices represent the ones set by expensive gas turbines that serve as peaking plants.**

These extreme fluctuations by power generators cause volatility in the electricity prices. **The main attempt of this study is to reduce an arbitrageur's or private entity's (an example of energy supplier is tajen in this study) exposure to volatility. This is suggested here by shaving the areas that contribute the most to price volatility.** Three cases can be devised to see how far this strategy holds true.

Assuming fixed and sunk costs of a storage technology to be constant, the variable costs (associated with buying electricity when the storage system is charging) and the revenues (associated with selling electricity when the storage system is discharging), are taken into account. The MCP set by the wholesale market is used by the private entity to purchase electricity. Electricity can be sold at all points on the Gaussian curve, since the 24 points represent the 24 hourly prices cleared in the day-ahead market. The main idea behind the strategy is to reduce the private entity's exposure to volatility, which is measured by the standard deviation σ. For this strategy to form a strong enough business case, it will also have to reduce the volatility that the end consumer is exposed to. It must be noted that volatility exposure faced by the end consumer can be eliminated at +1 σ, +2 σ or +3 σ, since this when the prices are the highest. The private entity on the other hand should be able to make use of the low/zero/negative prices, occurring at -1 σ, -2 σ or -3 σ, as a means to compensate for the risk that it will face by providing its service to the end consumers at +1 σ, +2 σ or +3 σ. Hence **it is assumed that the private entity would purchase electricity every hour in € at μ - 1σ, μ – 2σ or μ - 3σ, accounted as its variable cost and sell it accordingly at μ + 1σ, μ + 2σ or μ + 3σ respectively.** These three cases are compared below. This study uses volatility i.e. standard deviation, in the market to generate profit, which is taken as the difference between variable costs and revenues, as is mentioned in other studies [65]. The difference between variable costs and revenues is known as the contribution margin [65]. High/positive contribution margin, which is essentially the use of volatility to generate a profit, denotes the investment into energy storage to be performing economically well and vice versa.

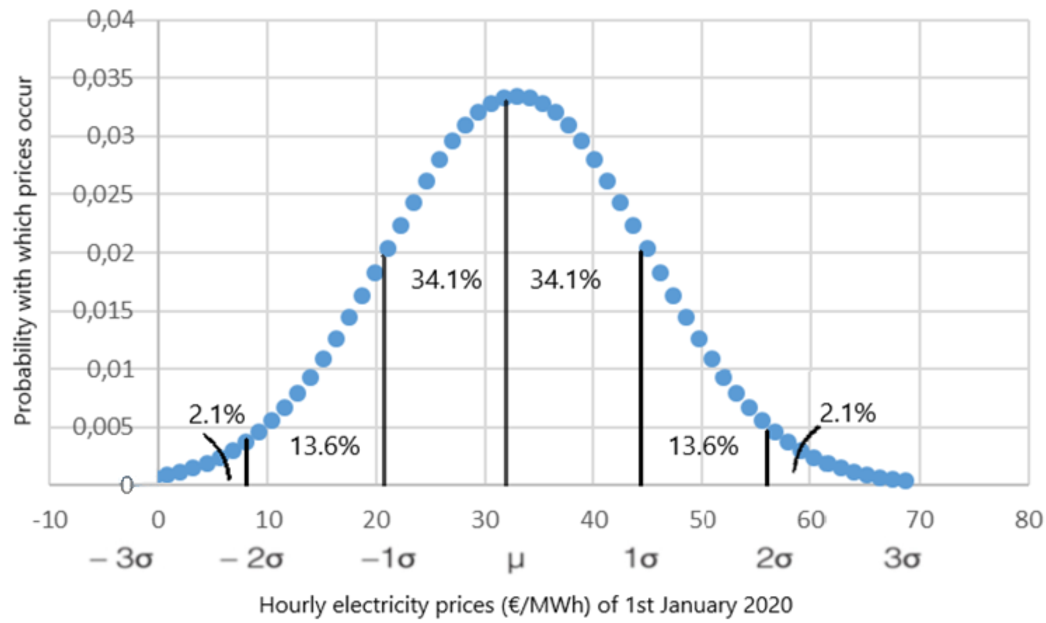

Figure 15: Hedging strategy implementation on hourly electricity prices in €/MWh of 01.01.20

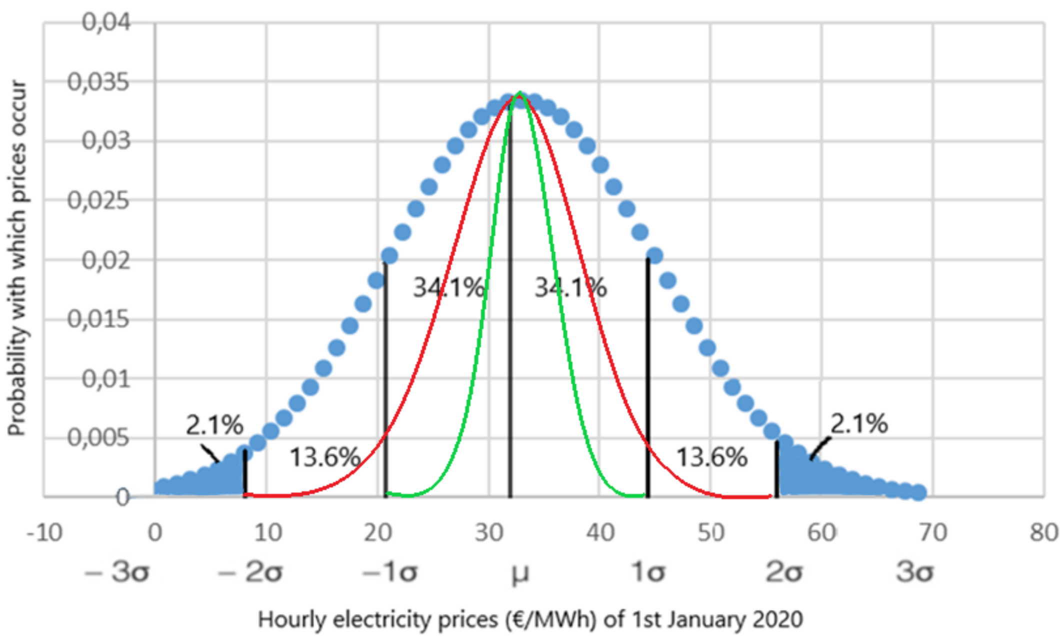

Figure 16: Normal distribution representation of hourly electricity prices in €/MWh of 01.01.20

Case 1: Shave off the area between -3σ and -2σ and +3σ and +2σ

In Figure 15, the red curve suggests that the area between +3σ and +2σ and -3σ and -2σ are eliminated. This implies that all prices that fall between these two intervals are removed and the price at which electricity is sold to the end consumer is confined to +2 σ, while the private entity utilizes the prices beyond -2 σ to charge, thereby making use of the extremely low prices. A new set of 24 prices are calculated and a new standard deviation is found for these new set of 24 points.

IF $P_i \geq \mu + 2\sigma$, THEN the revenue is limited at $\mu + 2\sigma$
IF $P_i \leq \mu - 2\sigma$, THEN the variable cost is limited at $\mu - 2\sigma$
ELSE
P_i is considered

Case 2: Shave off the area between -2σ and -1σ and +2σ and +1σ

Similar to case 1, in Figure 15, the area between +2σ and +1σ and -2σ and -1σ are eliminated, which means all prices that fall between these two intervals are removed. A new set of 24 prices are calculated and a new standard deviation is found for these new set of 24 points.

IF $P_i \geq \mu + 1\sigma$, THEN the revenue is limited at $\mu + 1\sigma$
IF $P_i \leq \mu - 1\sigma$, THEN the variable cost is limited at $\mu - 1\sigma$
ELSE
P_i is considered

Case 3: Shave off the area between -1σ and -$\frac{1}{2}$ σ and +1σ and +$\frac{1}{2}$ σ

Similar to case 1 and 2, in Figure 15, the area between +1σ and +$\frac{1}{2}$ σ and -$\frac{1}{2}$ σ and -1σ are eliminated, which means all prices that fall between these two intervals are removed. A new set of 24 prices are calculated and a new standard deviation is found for these new set of 24 points.

IF $P_i \geq \mu + \frac{1}{2}\sigma$, THEN the revenue is limited at $\mu + \frac{1}{2}\sigma$
if $P_i \leq \mu - \frac{1}{2}\sigma$, THEN the variable cost is limited at $\mu - \frac{1}{2}\sigma$
ELSE
P_i is considered

The results of Case 1, 2 and 3 have been computed hourly for each day and is depicted in the graph in

Figure *17*. It is evident that as the revenues are generated from higher standard deviations, higher is the profit generated.

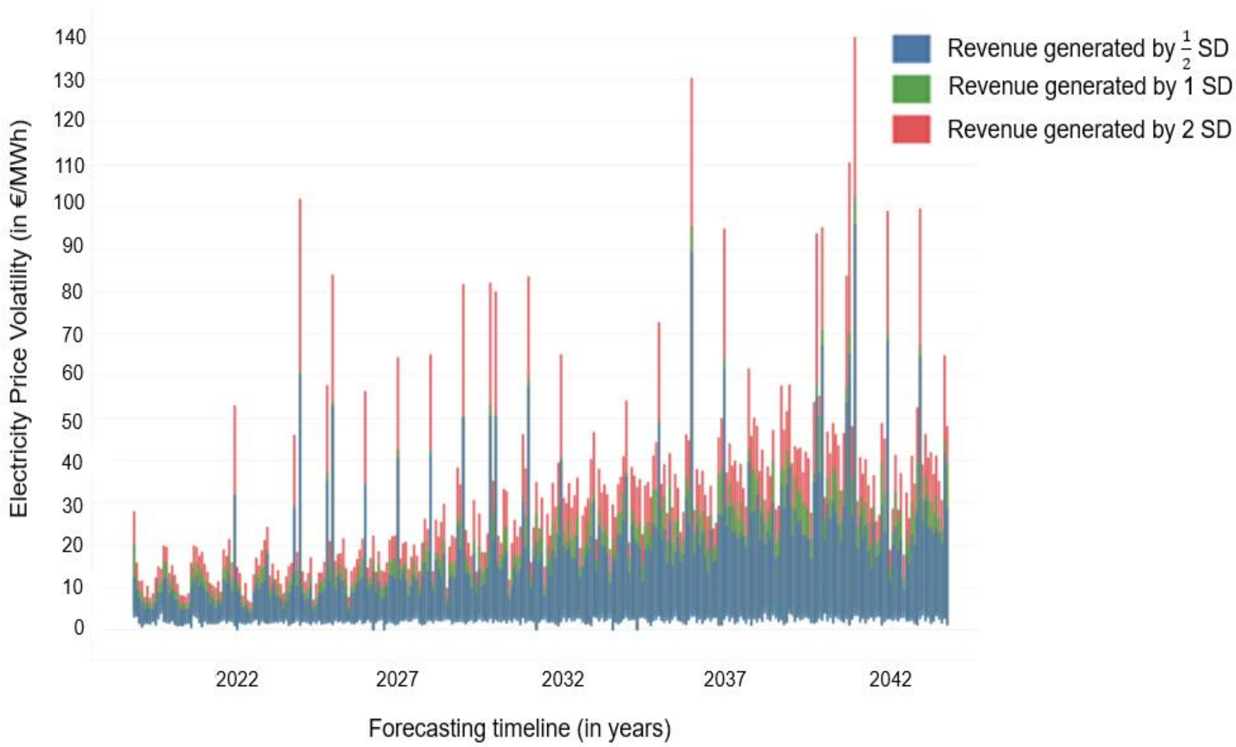

Figure 17: Electricity price volatility after hedging implementation (note: SD= standard deviation)

Since volatility is monetized in this strategy, it would mean that the farther is the standard deviation from the mean, the higher the contribution margin and higher is the possibility to generate profit. The main economic incentive for BESS in this study is to exploit the hours at which it is discharged and charged, giving no increased importance to either activity.

By representing the hourly electricity prices on a normal distribution curve i.e. the 24 points on the curve, the different percentages representing the areas under the curve can be used for a quick understanding of the number of hours it makes economic sense for it to charge and discharge. The charge and discharge hours can then be used to determine what would be a marketable battery size to invest in.

The three aforementioned cases give a very unpolished idea of how profitable the hedging strategy will be. This way of looking at the contribution margin will result in investment in a non-marketable size of the BESS, since it does not consider the number of hours at all. We know that 24 points (depicting 24 hours) of a day are arranged around the mean in steps of standard deviations. It is to be noted that these points are not arranged in ascending or descending order. As a result, the percentages represent the number of prices out of the 24 points that fall within a certain percentage interval, as seen in Table 4.

Table 4: Hedging strategy hours based on empirical formula

Standard Deviation intervals	Percentage under each interval	Number of points (out of 24) in each interval
Between ± 3σ and ± 2σ	2.1 %	≈ 0.5 points i.e. 30-min battery
Between ± 2σ and ± 1σ	13.6 %	≈ 3.5 points i.e. 3.5-hour battery
Between ± 1σ and μ	34.1%	≈ 8 points i.e. 8-hour battery

Seeing the percentages that explain the area under each part of the bell curve, it is evident that approximately 16% of the 24 points lie above +1 σ and below -1 σ, which amounts to 4 points (i.e. 4 hours). This would mean that the BESS can charge at $\mu - \sigma$ and can discharge at $\mu + \sigma$. Propelled by the results shown in

Figure *17*, to make higher profits, one would want to sell at $\mu + 2\sigma$. However, the percentage of values that fall after 2σ is only around 2% out of the 24 points, which amounts to 0.5 points (i.e. half an hour). A 30 minute BESS is not a marketable size, given its small capacity and also the percentage is too small to guarantee that the price point will occur at that level, with the probability being too low. Hence, the probability of revenue being a guarantee is definitely higher at 1 σ, giving a marketable battery size. The reason behind referring to a 30-minute BESS being non-marketable is because it does not make for a strong business case. Since the electricity market in focus in this thesis is the day-ahead hourly market, it is more convenient to utilize an entire hour worth of electricity. A 30-minute battery confines the private entity to use this BESS only during a part of the extreme peaking hour and off-peak hour, thereby leaving an interval of peak and off-peak hours unutilized. This sets a starting point to choose the correct type of battery technology.

Various optimization techniques can be used to maximize profits via arbitrage like Price-Based Unit Commitment (PBUC) [51]. This thesis does not intend to find the best allocation of resources, for example, the most optimized combination of energy and ancillary services, to reduce costs or maximize profit, but it attempts at providing a strategy to find the most suitable trading hours, so as to provide a higher incentive for the BESS to indulge in arbitrage and reduce the exposure of the arbitrageur to price volatility.

5

Suitable implementation scale for BESS

This chapter attempts to estimate the scale in the distribution grid that to allow the BESS make the most economical sense. In order to do this, an appropriate storage technology is first selected and the market size of the BESS is then estimated using the hedging strategy.

5.1 Motivation behind storage choice

Out of all the potential solutions to tackle generation intermittency, the most viable solution is ESS [66]. There is very little evidence in the immediate horizon to conclude that a solution revolving around storage has proven to be economically feasible and will become a norm when complimented with renewable energy penetration. Hence, it is extremely crucial for storage technologies to play a vital enabling role, to contribute to the fast pace at which carbon free electricity generation will be adopted.

Why BESS in particular?

It is essential for the reader to understand that energy arbitrage is not the only avenue for an ESS to be profitable. It is the chosen avenue in this thesis. Existing literature widely studies the technical benefits that BESS can provide, especially the grid applications of BESS [67] [68] [13] [69] [70] [66]. These benefits include ancillary services like frequency control, peak shaving and grid stability among many others. ESS can cover the entire electricity value chain- from generation to utility services and have been elucidated in the Figure 18 below. The economic benefits from the technical services that BESS provides is gradually beginning to be studied in detail [71] [72] [73] [74]. Out of the several financial benefits of ESS examined based on market analysis, this thesis focusses on a combination of two of them: revenue increase using energy arbitrage and revenue increase from RES [74]. The profitability of a BESS using energy arbitrage is evaluated, with the assumption that it in the event that it does not implement the hedging strategy, it can be used to provide services to the grid. These extra technical services depend on the agreements among various relevant stakeholders and will not be discussed in this report. The benefit from the frequently mentioned energy arbitrage is shown in the left side of Figure 18, where arbitrage is used to hedge risks posed by fuel price volatility. Since the future electricity market considered in this study is going to be RES-driven, “fuel” in the referred figure will be substituted with RES (mainly solar, onshore and offshore wind, for the purpose of this thesis).

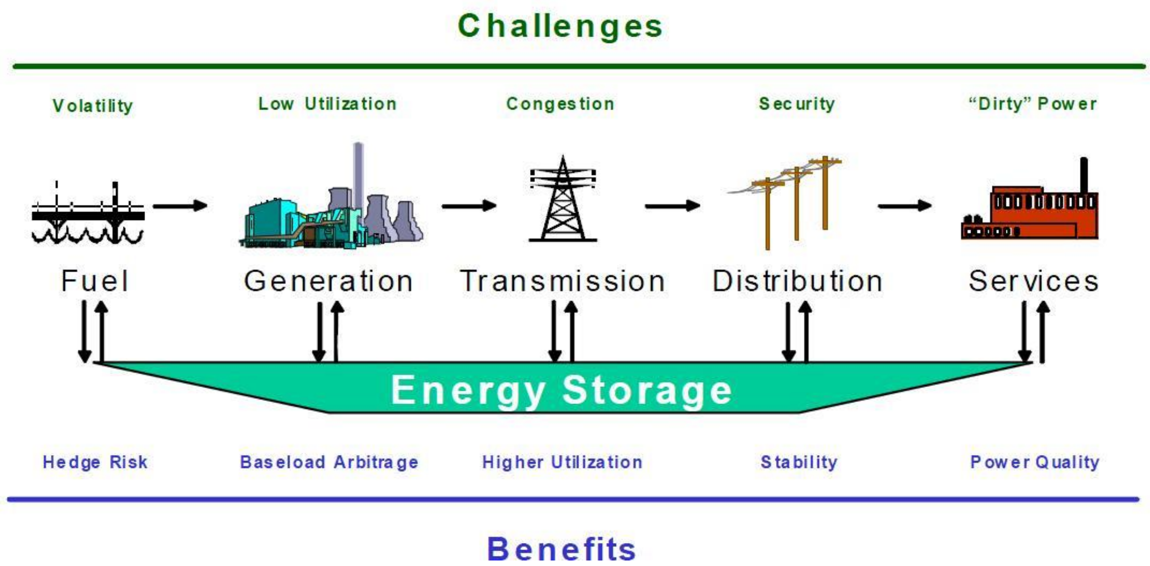

Figure 18: Benefits of ESSs across the entire electricity value chain *[75]*

The stationary energy storage technologies that hold the most promise for energy arbitrage are hydrogen storage, CAES, batteries and pumped hydroelectric storage [66].

Table 5: Comparison of four relevant stationary storage technologies

	Maturity of technology	Focus areas	Geographical limitations	Response time	Societal issues
CAES	Not fully mature	Large scale, centralized use	Suitable for developed countries	1 minute	Low concern
U-PHS	Immature	Large scale, centralized use	Suitable for flat-land countries (like The Netherlands)	10 minutes	Medium concern
Hydrogen storage	Not mature	Both large and small scale use; centralized/decentralized use possible	Not limited by geological requirements	100 millisecond	Medium concern
Batteries	Li-ion is mature, NaS is relatively mature, Flow not as mature	Both large and small scale use; decentralized use preferable	Not limited by geological requirements	1 millisecond	Low concern

These four technologies are compared in brief in Table 5, based on technological maturity, most applicable areas, geographical limitations, response time and societal issues. Societal issues refer to how socially acceptable the technology is (based on environmental impact, aesthetics, whether people in the vicinity will agree to accept it etc.). Response time in an ESS is the amount of time required for the system to begin releasing power. Since the hedging strategy proposed is for a dynamic, unpredictable RES-driven distribution grid, the storage technology will have to be extremely responsive, hence the focus on response time.

Two key factors were taken into account to shortlist the aforesaid technologies for energy arbitrage to be profitable:

a) The technologies must comply with the required minimum charging/discharging duration; a significant energy arbitrage requires a minimum discharge duration of 1 hour [74].

b) The technologies must comply with the hedging strategy condition- as discussed in Chapter 4 and in Table 4, the minimum required hours for the hedging strategy to work is 1 hour.

Reasons behind choosing the distribution grid to formulate the hedging strategy

Since CAES is applicable mainly for large-scale centralized operations and U-PHS is still under development, hydrogen storage and batteries would make two good set of choices. It should be emphasized as to why large-scale applicable storage technologies were not chosen. The scope of this thesis was confined to the distribution grid due to the increasing complexities that this section of the grid is facing. A crucial actor in the distribution grid, the DSOs, are dealing with a higher ingress of power and utility entrants like DERs and EVs, and they have to constantly make sure that the distribution grid has enough capacity to accommodate these technologies and can reduce peak usage [76]. With the increase in DERs, the gap between demand and energy availability can constantly change, posing concerns to the grid stability and reliability. DSOs are looking to change their roles from being asset-oriented to becoming service-oriented [77], but the lawful requirement of the DSOs as being unbiased will make this shift in roles trickier, providing an opportunity for solutions in this domain. Ever since liberalization, the distribution grid is more open to competition in the market level, from the electricity markets to the retail market. The increase in competition in the retail market space has provided consumers with more choice, and they are no longer obliged to stick to one supplier after their contract periods. With an increase in RES in the grid, this would put an onus on the energy supplier/energy supplier to provide the most competitive rates. In order to do so, they would look to decrease the risks caused by a RES-driven electricity price volatility at the wholesale market, hence providing better rates at the consumer level. A strategy to aid the latter is pursued in this thesis.

Reasons behind choosing Lithium ion as the BESS

Table 5 elucidates that batteries are going to be the choice for the stationary ESS that fulfils the conditions required to use the hedging strategy proposed in this thesis. Various stationary battery storage technologies are currently present in the market, out of which Li-ion batteries are selected as the BESS. At a theoretical level, different battery energy storage options can be compared using an application based classification, depending on their discharge times at rated power and the system power ratings [78]. Three different applications are taken into account:

- ability of the ESS to increase power quality
- load shifting ability from peak to off-peak hours and vice versa
- ability to manage large amounts of power

For stationary ESSs, features like high cycle efficiency, low maintenance, increased life span, smaller size, modularity and scalability are considered favorable. Li-ion BESS proves to be the first choice that satisfies all criterion. Recent years have seen an increasing market for Li-ion batteries in the energy sector. Li-ion storage devices have experienced rapidly lowering costs, have excellent charge retention, high cell voltages, very good low temperature performance, long cycle life, and high depth of discharge, and will be the chosen storage technology in this report. The costs and benefits of using Li-ion batteries in a distribution network from the end-user point of view is examined in [79]. Flow batteries and NaS batteries are the other type of batteries that have been claimed to compete with Li-ion batteries. In some instances, they seem to have a lower degradation than Li-ion and are sometimes safer, but has not been tested yet [80]. Flow batteries are generally not as well studied as Li-ion and are very energy dense (they need a larger surface area to employ), and these were the main reasons behind not considering them for the hedging purpose in this thesis [81]. Li-ion is also considered better for long duration and the charging/discharging hours can be scaled by adding more or less of them [80]. NaS, despite its fairly low cost, still could not outstrip Li-ion as the choice for BESS in this thesis, due to the high temperatures required for operation and toxic materials in their makeup [81].

5.2 Profitability of energy arbitrage through BESS

In the previous sections, it was touched upon that energy arbitrage is the chosen avenue for profitability of a BESS. However, there are several kinds of arbitrages. This section explains the various types of arbitrages that are typically employed and which one makes the most profitable sense for the purpose of this thesis.

For any storage technology project to be a commercially viable project, it must be economically feasible with a rational rate of return on investment. Profitability of arbitrage in energy storage has been assessed across different literatures. These studies are based on storage facilities that are classified by three major characteristics irrespective of the technology [82]:

- power capacity (denoting amount of hours of full power output, expressed in MW)
- energy capacity (expressed in MWh)
- efficiency factor (denoting the losses sustained during charging and discharging cycles, and/or also the amount of hours it can provide full output)

These studies are further divided into whether the storage facilities are price takers or price makers. Price-taker storage facilities do not affect the market price upon their operation. The value generated out of the energy storage facility is small compared to the market supply or demand and the value of such a system various states across the U.S.A. is discussed in [83]. The impact of energy capacity and efficiency on the value of small energy storage is estimated and the effects of fuel prices on the arbitrage value is examined as well. It was found that hourly peak prices are usually decided by baseload generation like natural gas, hence as the price of fuel increases, so does the value of storage [83]. [84] examines the economics of storage technologies suitable for small scale energy storage, like sodium sulphur batteries and flywheel ESSs, in the New York electricity market. It was found that both these storage technologies had a high probability of positive NPV for energy arbitrage. When large storage systems, on the other hand, charge during off-peak time and discharge during peak time, they may decrease the price gap and impact the supply and demand of the market in which they function. Accounting for the effect of storage operation on the price becomes crucial to evaluate the potential profits from large scale storage [82].

As discussed previously, the main way in which storage technologies can create value is through arbitrage i.e. by cashing in on price variations in the electricity market after shifting production/ consumption patterns from surplus to deficit or vice versa, thereby hedging against market risk (theoretically). The difference between peak and off peak day-ahead market prices can be capitalized upon.

There are two kinds of arbitrage opportunities in the electricity market: Same-Commodity arbitrage and Cross-Commodity arbitrage. Same-commodity arbitrage, as the name suggests, only uses one type of commodity (i.e. electricity) and will be focussed on in this thesis. It can be found by examining either temporal or spatial arbitrage in day-ahead electricity markets. Spatial arbitrage is possible in interconnected cross-border electricity markets, where price differences across various markets are taken advantage of and is based on current information. Since this thesis does not cover cross-border exchanges within its scope, temporal arbitrage will be at the focal point. Temporal arbitrage is based on the theory that upon analysing historical information, a commodity is stored today to be used in the future when the electricity price is expected to be higher in the and the difference is higher than cost of storage and transportation [85]. In this thesis, profit maximization is the main operational strategy behind temporal hedging, by focussing on the value of flexibility that energy storage can create. As much as there is a need for storage, this need can reduce in certain instances as well, like by spatially diversifying the RES upon increasing the capacity (and assuming that these resources will be stochastically independent or have negative co-variances) and the increasing efficiency of DSM [86]. There is plenty of literature that acknowledges different issues related to energy storage. Spatial and sizing issues of different storage technologies, while focussing on reducing system-wide operation and capital costs, has been studied [73]. Value of arbitrage for energy storage using electricity prices is studied as well [32], based on various methods measuring profitability, like IRR. Due to the scope of this study, we take into account a generic storage device described only by its capacity and power constraints and efficiency.

This thesis focusses on BESS to not influence the market prices as it is implemented in a relatively small scale. It is clear that temporal hedging within same-commodity arbitrage is the chosen means of energy arbitrage using Li-ion BESS, of varying power and energy capacity ratings but same discharging/charging hours.

5.3 Motivation behind the choice of economic measure for BESS economic feasibility

In this study, different storage solutions (different on the basis of varying scale-appropriate ESS ratings) of the same storage technology (i.e. Li-ion) are used to compare different levels in the distribution grid. In order to understand the level at which installing the Li-ion BESS makes financial sense, an economic feasibility using NPV and IRR is conducted. These different storage solutions have to comply with the hedging strategy condition i.e. the amount of time required to charge and discharge differently rated power ratings should be minimum 4 hours (seen in Chapter 4), thereby giving the investor the choice of battery capacity that falls within their financial constraints.

Assessing the cost of an energy storage project cannot be based on a standard economic measure as the value possessed by an ESS heavily depends on the prevalent conditions under which it operates [72].

Different BESS applications have different revenue streams. For example, if a storage system is operating in the peak shaving mode, the value it possesses will depend on the difference between cost of purchasing the power during off-peak time and revenue from selling the power during peak-time. If a storage system provides ancillary services like offering grid stability or power conditioning, the value it possesses will be dependant on the losses to the grid the ESS help avoid if the grid had become unstable or had the power quality decreased. Several studies that analyse ESS economics use costing as their main quantifying factor [87].

Among various economic metrics for an energy project evaluation, some are [88]:

- Payback time – the time it takes to gain the returns from an investment
- Net present value (NPV) – accounts for the time value of money by discounting future cash flows occurring at different periods to a present value
- Internal rate of return (IRR) – evaluates the degree of profitability of potential investments by measuring the rate at which a project breaks even.
- Levelized cost of electricity (LCOE) – the expected revenue per unit of electricity generated, that is required to recover the costs of investment in operating and building the infrastructure for electricity generation, during its lifecycle

Usually, many papers pitch different economic measures against each other without realizing that not all economic metrics can be used for every case. There exist literature that state that LCOE, for example, possesses way more accuracy in measuring the profitability of a project compared to NPV [89]. However, it must be noted that LCOE gives a measure of cost of electricity whereas NPV gives a measure of invest-ability of the entire project lifetime [90].

The choice of economic measure also varies with the input data available [90]. If the price to purchase power is not known (resulting in a failure to calculate revenue), LCOE is the ideal preference of economic metric used by decision makers [90]. LCOE is more isolated from the financial/taxation/legal factors than NPV or IRR, while NPV, IRR or both has a better focus on the financial/taxation aspects. If the project is technology-focussed and has to take into account various technical parameters and externalities, then LCOE is a good measure. However, if the project is in the phase of research and development (R&D) where investment-focussed decisions based on a technology, to attract shareholders, have to be made, then NPV or IRR proves to be a better choice [90].

The economic rationality behind the choice of BESS at different levels in the grid is explained using NPV over the BESS lifetime in this thesis. A storage source is not a generation source. In the case of this thesis, it merely stores electricity when the electricity price is low (i.e. when supply is greater than demand) and releases electricity when the electricity price is high (i.e. when demand is greater than supply). If LCOE is used to calculate the cost effectiveness of a BESS, given its high capital costs, the LCOE will definitely be higher when compared to the generation resources, but it does not take into consideration the services that a BESS can provide like ancillary services or the uncertainty in revenue generated out of projects [91]. Hence, LCOE is not particularly accurate in calculating the cost-effectiveness of BESS since it is a characteristic standard for calculating the cost of generation resources and does not take into account the revenues generated every year. The profitability of ESSs should be considered on a project-specific basis, which can be done through techniques like IRR and NPV of both the expected costs and benefits and the investment cost of storage at different scales in the distribution grid.

Net Present Value

To calculate NPV, an interactive storage tool on Microsoft Excel was created and was used for the modelling of the business case of BESS in different scales in the distribution grid, that provides the user with a thorough analysis of NPV components, IRR and cash flow over the lifetime of the project. This tool was designed to help the stakeholders visualize the returns from an energy storage project at different points in the grid. This thesis focusses on energy arbitrage as the main revenue creation, hence it will be assumed that the storage system does not provide any secondary applications, while acting as an arbitrageur, for solely calculation purposes. Beyond calculating the economic metrics for this thesis, it can provide any ancillary service, depending on the agreements that the private entity can form with relevant stakeholders. This tool allows users to specify key parameters that the tool controls with respect to the energy storage project or make changes to the pre-defined set of parameters. These parameters include features like technology efficiency, capital investment and tax subsidies. The mathematical formulation is presented in equation (17 [90], where FV refers to future cash flows, 'i' refers to a discount/interest rate and 't' refers to the number of periods in the FV cash flow.

$$\mathrm{NPV} = \sum_{t=1}^{n} \frac{\mathrm{FV_t}}{(1+i)^t} \tag{17}$$

The discount rate is the annual interest rate employed to reduce/standardize the amounts of future cash flows to give their present value. This value is not easily assessable and varies depending on the energy source and the country of deployment. Many studies use a higher discount rate to account for risks.

Internal Rate of Return

IRR is the measure of the discount rate used in NPV that yields an exact zero value of NPV, satisfying equation (18 [90].

$$\mathrm{NPV} = \sum_{t=1}^{n} \frac{\mathrm{FV_t}}{(1+i)^t} = 0 \tag{18}$$

Calculation of IRR was embedded into the interactive storage tool that was created for NPV on Microsoft Excel. Including IRR into the interactive tool provided a holistic view on the business case of BESS in different scales in the distribution grid. It is evident that higher the IRR, better is the investment. Both the IRR and NPV together form the breakeven point analysis for the BESS.

In this thesis, the breakeven point analysis for BESS is presented through a scenario analysis, where the basis all of the scenarios being that the stationary Li-ion BESS in the distribution grid will be used to store electricity during low electricity price volatility and release electricity during high electricity price volatility.

5.4 Methodology for choosing the scale in distribution grid

The economic metrics discussed in the previous section are used to assess different scales in the distribution grid. Energy arbitrage using hourly electricity price volatility will be examined across various system sizes of the same storage technologies at different scales in the grid to help understand financial effects pertaining to the same technology. These different scales refer to different scenarios and the economic metrics in different scenarios are calculated based on the following factors:

- Power rating – refers to the rated maximum power rating of the BESS in MW
- Energy capacity – refers to the maximum rated energy capacity that the BESS can hold in MWh
- System efficiency – refers to the amount of useful energy lost during operation in %. With the advancements in integrating Li-ion technology into grid connected BESS, the current efficiency is at 90-95% [81]. However, an 89% efficiency is considered in this thesis to be on the safe side.
- Capital investment – probably the most important parameter in NPV and IRR analysis, it gives the capital that was invested up front to set up the BESS
- Discount factor – refers to the rate in % employed to discount future cash flows to determine the present value
- Taxation – refers to the tax rate in % that the government levies on business that incur a certain profit annually. The Dutch government excises a 19% corporate tax on yearly profits less than €200,000 and 25% above this threshold [92]. In 2021, it decides to decrease the taxes charged to 15% for annual profits below €200,000 and to 20.5% otherwise [92]. The taxes are even lower on renewables projects in the Netherlands, however storage projects are not recognized as a part of renewables projects yet. This points to the fact that the business case mentioned in this report will only get more attractive in the future upon policy changes.
- Savings of the consumer – This is based on the benefit that the end user of the hedging service will face. The benefit is in the form of the cost not paid to the grid in times of highly volatile prices (avoided cost), but utilizing electricity provided by the BESS at $\mu + 1\ \sigma$.

Based on the above factors, the following are calculated for the estimation for NPV and IRR.

- Revenue (in €) – Yearly revenue or more precisely, the gross profit, is calculated using volatile prices. In the case of the hedging strategy proposed (i.e. a 4-hour hedge), it was found that the BESS would charge (will buy from wholesale market) at $\mu - 1\ \sigma$ and can discharge (will sell to the receiving consumer) at $\mu + 1\ \sigma$, giving a profit worth $2\ \sigma$. Hence revenue/gross profit is found by multiplying the hedge hours (4, in the below mentioned scenarios), the profit valued at $2\ \sigma$ (calculated using the volatility equations mentioned in Section 3.3) and the amount of electricity (denoted by peak power rating) used to make this profit. Since no energy storage is a 100% efficient yet, losses during the charging/discharging has been taken into account in the form of system efficiency. The peak power is used to calculate the revenue, after multiplying by the system efficiency.
- Consumer benefit (in €) – This is the benefit that the end user of the hedging service will face. The benefit is in the form of the cost not paid to the grid in times of highly volatile prices (avoided cost), but utilizing electricity provided by the BESS at $\mu + 1\ \sigma$.
- Costs – Annual costs, includes one combined figure for all costs suffered like O&M costs.
- Cash flows – Annual profits that the private entity is rewarded with upon utilizing the most and least set of 4 hourly volatile prices.
- Cumulative cash flows – The combined cash flows found by adding all cash flows from the time the company began, this includes the capital cost as well.
- Service fee - The supplier is assumed to charge a service fee of 50% of the savings to the consumer to account for the overall investment expenses in the BESS.

Scenario 1: Large-scale (MW scale) BESS in the distribution grid

In the first scenario, the economic performance of a Li-ion large-scale storage system is simulated over a lifetime of 15 years, wherein at the end of this period the battery is decommissioned and sold at half its cost. The storage system is a Li-ion battery of a rated capacity of 4 MWh, which is connected at the largest distribution grid level and this energy storage project has the following specifications:

Maximum power rating – 1 MW [93]
Rated energy capacity – 4 MWh [93]
System efficiency – 89%
Capital investment - €600,000 [93]
Recovered cost upon decommissioning - €300,000 (an assumption)
Discount factor – 3% [92]
Taxation – 81% [92]

At this level, electricity is purchased at whole-sale prices and sold to retail companies at whole-sale prices. With the 4 hour hedging strategy discussed above, a cost analysis is carried out on the storage system. The results of this analysis are mentioned in the Figure 19 below. The graph shows the progress of the storage system, with profits (after taxes) from the sale of electricity serially added to the initial investment costs. The NPV of the project is approximately a little above €54,200, while the IRR is a negative figure for the estimated lifetime of the battery system of 15 years. The large scale (also known as the MW scale) system, on account of the low prices of the wholesale market, was deduced to be infeasible for private investment.

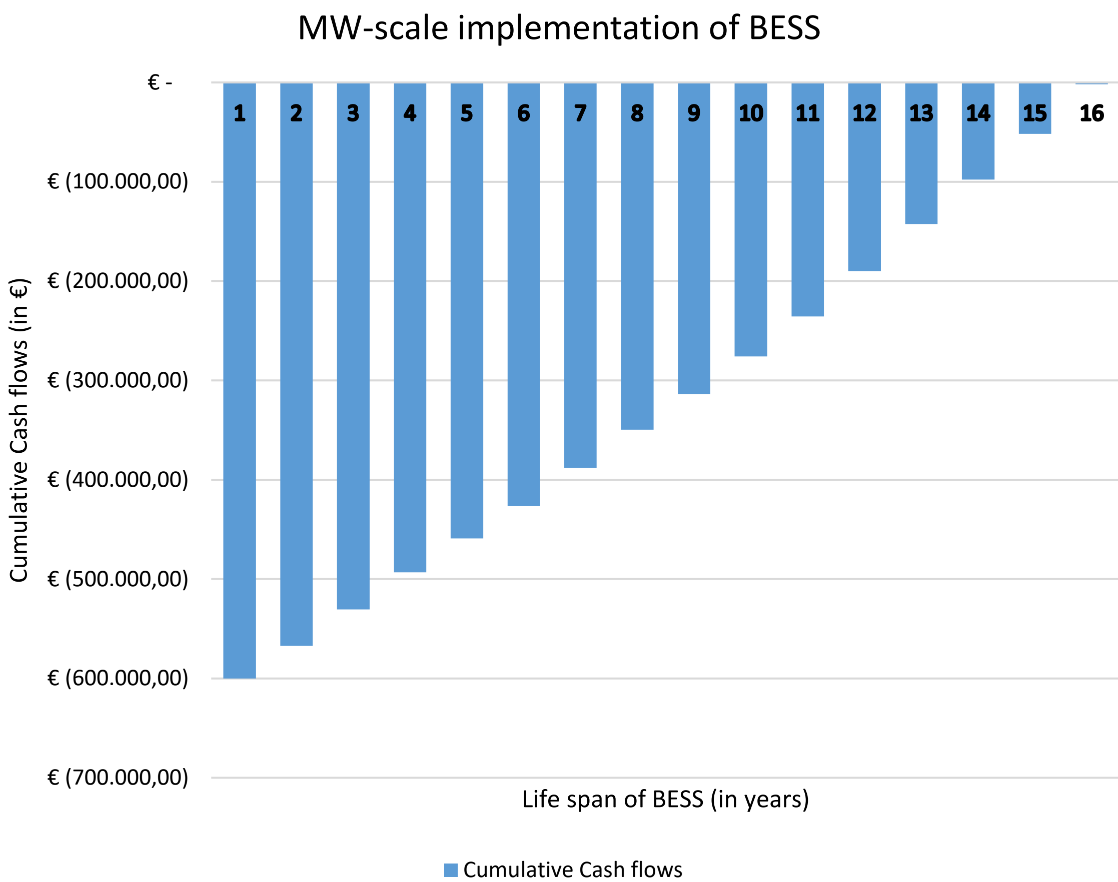

Figure 19: BESS breakeven-point analysis at a large-scale level

Scenario 2: Small-scale (Home scale) BESS in the distribution grid

In the second scenario, a small scale storage system is considered. This system is the Tesla Power Wall, and it operates at a household scale where electricity is exchanged with homeowners at retail electricity prices. This BESS project has the specifications mentioned below. The cost analysis as carried out in Scenario 1 can be seen in Figure 20, which shows the progress of the project over a span of 15 years. The NPV of the project is approximately €307 with an IRR of 3%. Due to the high capital cost of the Power Wall, the payback period is a little above 15 years, and hence not the most viable option for private investment.

Maximum power rating – 3.3 kW [94]
Rated energy capacity – 13.2 kWh [94]
System efficiency – 89%
Capital investment - €10,000 [94]
Discount factor – 3% [92]

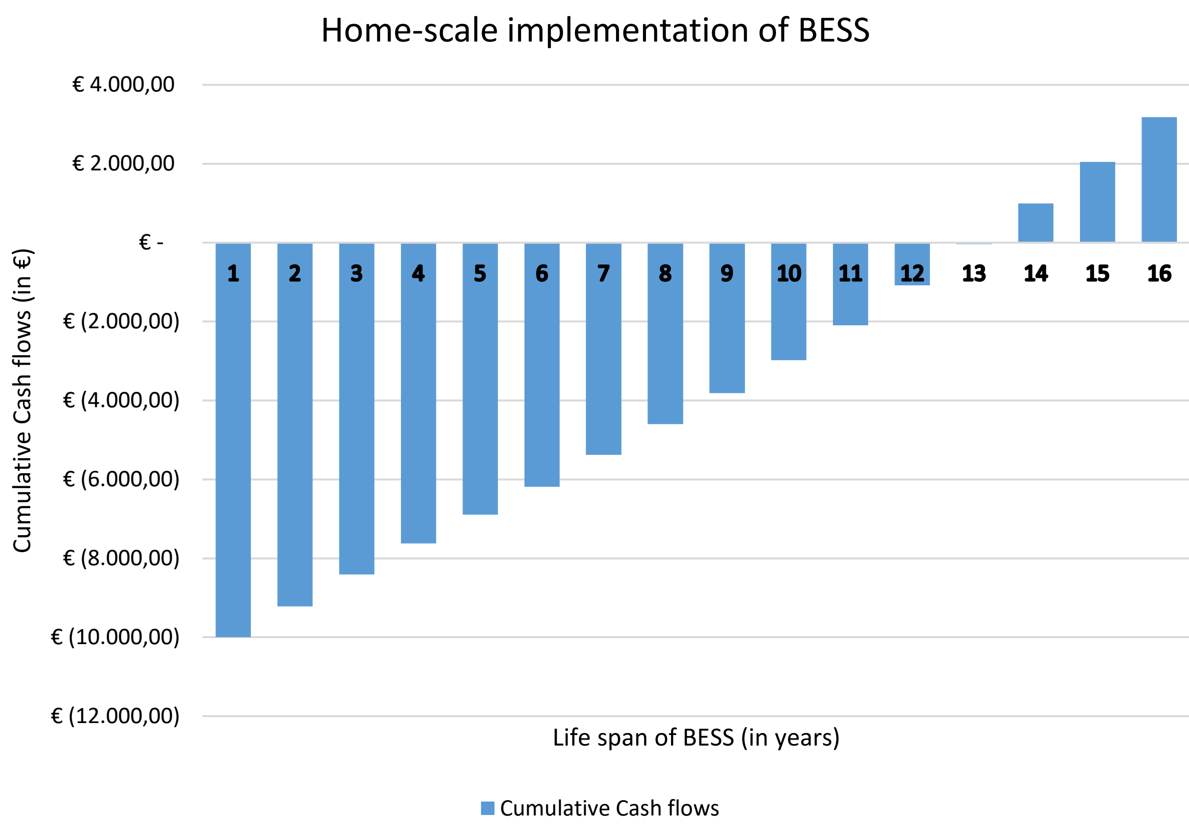

Figure 20: BESS breakeven-point analysis at a small-scale level

Scenario 3: Intermediate-scale (Community scale) BESS in the distribution grid

The third and the final scenario consists of an intermediate scale Li-ion storage system, which is at a community level. This system is a Tesla Powerpack and is assumed to operate at the community grid level and is thereby an acceptor of retail level prices. These prices are assumed based on an observed relationship between whole-sale and retail prices. Simulating the project economics for this system yields the cumulative cash flow curve as shown in Figure 21. It can be seen that the simple payback period is around 11. years. Meanwhile the NPV of the project is around €32,900 and the IRR is 8%. With these figures, the business case for the intermediate scale system appears viable. However, to ascertain the claim with certainty a risk analysis for the proposed strategy is necessary.

Maximum power rating – 52.5 kW [95]
Rated energy capacity – 210 kWh [95]
System efficiency – 89%
Capital investment - €70,000 [96]
Discount factor – 3% [92]
Taxation – 81% [92]

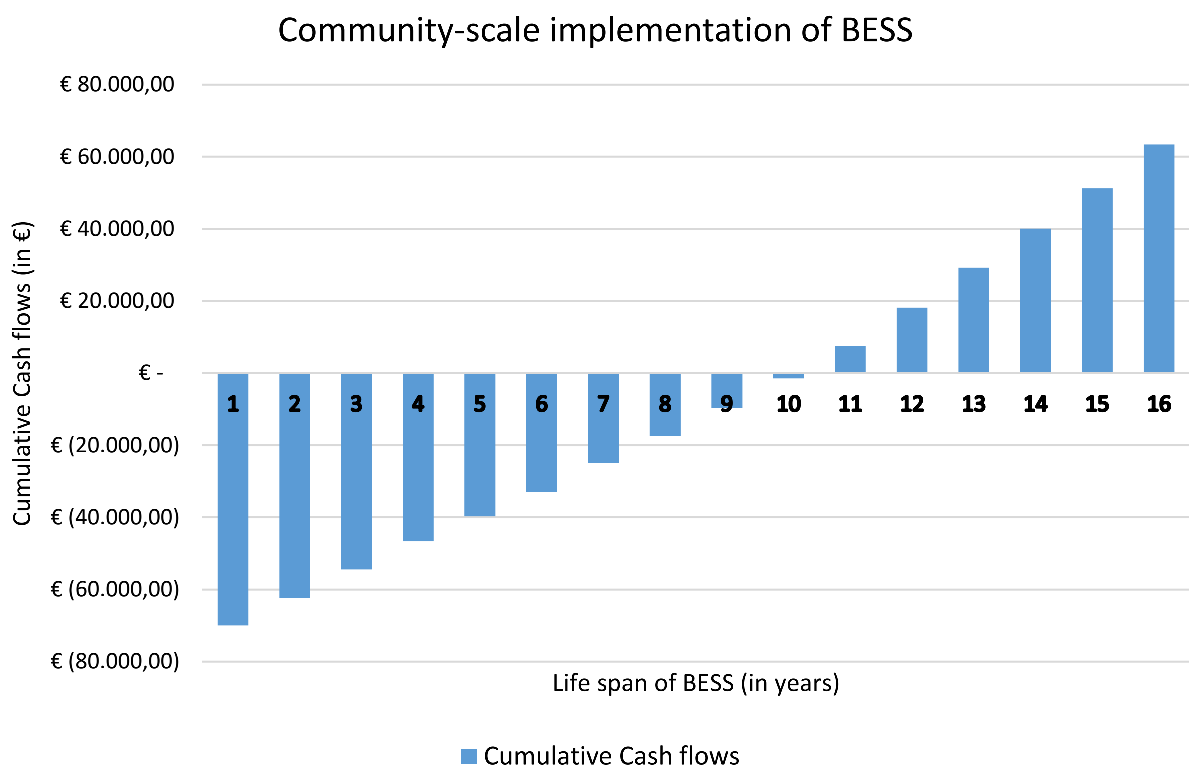

Figure 21: BESS breakeven-point analysis at intermediate-scale level

It is imperative to understand that variations in the wholesale prices (hence, also the electricity price volatility) has a direct effect on the arbitrage values. There is a possibility that the ideal number of hours may not be 4 the entire time, leading to the hedging strategy rendering futile. However, the hedging strategy is made stronger by the findings of the literature [97], which concludes that almost 90% of the total invested value is regained with just 4 hours of the ESS. Beyond six hours of storage, there is limited marginal value in extending the amount of storage with the additional storage providing only limited incremental arbitrage opportunities. For technologies with low installed capacity cost ($/kW) relative to energy storage costs ($/kWh), systems with a small amount of storage (in hours) may be more economically viable. A technology with relatively high installed capacity costs may opt for a larger amount of storage (in hours). The interaction between arbitrage opportunity and technology cost structure is beyond the scope of this thesis.

It is impossible that throughout the next 25 years, every day will perfectly follow the 4-hour hedging strategy condition, as unpredictability in electricity prices will prevent the probability distribution to be always normal. The factors taken to come up with an hourly electricity price forecast are also subject to change, like changes in RES penetration or change in demand etc. The risks posed from the non-normal distribution aberration and changes in RES penetration or demand will definitely be felt by the arbitrageur and it is necessary to quantify these risks, which is done in the next chapter.

6 Risk Assessment

One of the most important advancements in liberalization of electricity markets across Europe has been the development of power trading and risk management. When the markets were deregulated, the level of competition at every level in the grid was almost non-existent with markets operating at pre-set prices and fixed customers. With the increase in competition, customer choice and diversification of energy mix, price volatility has increased, placing a growing significance on risk management and hedging. Hence, it was deemed necessary to conduct an assessment of the risks posed on the private entity in cases where hedging strategy conditions cannot be met. This chapter analyses the risk posed on the arbitrageur or private entity that implements the proposed hedging strategy. Since the strategy in itself was a heuristic analytical approach, a similar path has been taken to quantify the risks posed on the arbitrageur in the events that the hedging strategy cannot be implemented.

6.1 Possible risk factors for the stakeholders

The electricity market is known to be substantially more volatile than any other commodity market. The uncertainty in market prices caused by increased RES penetration will only increase the electricity price volatility, and this has driven the various relevant market participants to recognize the need for risk management. Apart from this, introducing new technologies or potential new means to modify an existing technology poses new or potential risks. Risk in an electricity market, from the standpoint of the scope of this thesis, can be considered as both, an opportunity and a challenge. Any price movement that may be unfavourable to one market participant can be useful to another, thereby volatility is always perceived differently by different relevant entities.

Various factors affect the setting of hourly electricity prices, thereby affecting the risk posed. Weather changes are known to have a growing influence on average daily day-ahead electricity market in the Netherlands, as shown in [98]. As the wind or solar capacity increases, the supply curve shifts to the right as the marginal costs of producing electricity from these sources being very low. As the RES penetration into the grid increases, electricity price may start getting more linked to weather conditions than marginal costs set by fossil fuels, relating climatic changes and electricity prices very closely. Fluctuations in weather conditions will influence the price volatility as well, such that high solar irradiation or abundance in wind will lead to almost zero electricity price and unfavourable wind or solar conditions can cause high positive spikes in electricity prices. Price dynamics also depends on market response, depending on every day activities in off peak and peak hours, weekends and holidays, all of which have a very fickle nature, leading to fleeting price spikes. This will make predicting weather-related risks increasingly difficult. The Netherlands accounts for the majority of Germany's cross border exports, with 12.7TWh flowing to the Dutch Power Grids as of 2018 [99]. Due to this close connection with the German electricity market, the factors in Germany can also pose a risk while trading in the electricity market in the Netherlands.

The purpose of this study is not to elaborately discuss the various kind of risks that is faced in the electricity market, but to find a way to quantify the risks during anomalies encountered in the hedging strategy conditions. Two possibilities of events that can occur in which the hedging strategy conditions will not hold true have been considered.

1. Changes in renewable energy mix in the future electricity domain

   The hourly electricity prices forecasted in chapter 3 are strictly based on the historical hourly prices from 2014-2018. This forecast could have been made more accurate or advanced by using other exogenous variables like changes in solar energy penetration in the future or wind penetration in the grid, but the complexity of such intricate data analytic predictions are beyond the scope of this thesis. However, it is very likely that the RES grid penetration will change by a certain factor or percentage during certain intervals, say weekly, monthly or annually, into the future in order to meet the various energy targets set by the Dutch government. These changes in the energy mix will change the price forecasted and this brings up the question of whether the hedging strategy will still hold true.

2. Days where hourly prices do not follow a normal distribution

   The hedging strategy has been designed under one main condition – the hourly prices of a day follow the normal distribution. Given the increasing weather and price correlation and the uncertainty caused by renewables, there is a chance that the hourly prices do not even approximately fit into a bell curve [53] [47]. There are times when the prices are heavily tailed, right-skewed or do not resemble any prominent probability distribution [52]. Evaluating whether an alternative hedging strategy can be designed in such a scenario is extremely important for the private entity or arbitrageur to have a strong business model.

6.2 Risk 1: Changes in renewables grid penetration

The hourly electricity prices that were used to forecast future hourly day-ahead market prices of the next 25 years were extracted from ENTSOE’s Transparency Platform. This dataset comprised of hourly prices in €/MWh and was set as a result of various factors, like the aforementioned ones, that affect the market clearing price. This study assumes the forecasted prices to also be set by all the factors that set the historical data in the first place. However, it is optimistic to assume that the trends followed by various factors will follow the same trajectory in the next 25 years, as they did from 2015-2018. Changes in these factors will affect the prices, followed by a significant effect on electricity price volatility, exposing the private entity to unknown risks. In order to quantify these risks and see how the prices will be affected, an analytical risk analysis has been carried out below, based on a scenario proposed by the most recent *Klimaatakkoord elektriciteit* and an internal PwC report that explains yearly change in RES mix to achieve 100% energy transition.

Out of the several factors that affect the wholesale electricity price, the following were taken into account. Since this risk assessment only takes into account a change in renewable energy mix in the Netherlands, out of the several energy sources predicted to contribute to a 100% energy transition, the top three are chosen [100] [4].

- Hourly solar energy grid penetration in MW
- Hourly onshore wind energy grid penetration in MW
- Hourly offshore wind energy grid penetration in MW
- Hourly energy consumed in MW

Two basic assumptions are made in this risk assessment:

Assumption 1: All electricity generated is consumed, ignoring losses like line losses etc.
Assumption 2: An annual percentage increase or decrease of the renewables penetration is uniformly distributed and applied to each hour as well.

The methodology followed for this risk analysis is shown in Table 6. The methodology is illustrated in the form of equations (see equations (19(20(21) for the case of changes in annual solar penetration.

$$\Delta \mathrm{SolarMW}_{m} = \alpha_{\mathrm{solar,m}}.\mathrm{SolarMW}_{\mathrm{m-1}}.\mathrm{h} \tag{19}$$

$$\alpha_{\mathrm{offset,solar,m}} = \alpha_{\mathrm{solar,m-1}}.\Delta \mathrm{SolarMW}_{m} \tag{20}$$

$$\mathrm{P}_{\mathrm{m,new}} = \mathrm{P}_{\mathrm{m}} + \alpha_{\mathrm{offset,solar,m}} \tag{21}$$

The equations below also take into account offshore and onshore penetrations into the grid.

$$\Delta \mathrm{OffshoreMW}_{m} = \alpha_{\mathrm{offshore,m}}.\mathrm{OffshoreMW}_{\mathrm{m-1}}.\mathrm{h} \tag{22}$$

$$\alpha_{\mathrm{offset,offshore,m}} = \alpha_{\mathrm{offshore,m-1}}.\Delta \mathrm{OffshoreMW}_{m} \tag{23}$$

$$\mathrm{P}_{\mathrm{m,new}} = \mathrm{P}_{\mathrm{m}} + \alpha_{\mathrm{offset,offshore,m}} \tag{24}$$

$$\Delta \mathrm{OnshoreMW}_{m} = \alpha_{\mathrm{onshore,m}}.\mathrm{OnshoreMW}_{\mathrm{m-1}}.\mathrm{h} \tag{25}$$

$$\alpha_{\mathrm{offset,onshore,m}} = \alpha_{\mathrm{onshore,m-1}}.\Delta \mathrm{OnshoreMW}_{m} \tag{26}$$

$$\alpha_{\mathrm{offset,onshore,m}} = \alpha_{\mathrm{onshore,m-1}}.\Delta \mathrm{OnshoreMW}_{m} \tag{27}$$

$$\mathrm{P}_{\mathrm{m,new}} = \mathrm{P}_{\mathrm{m}} + \alpha_{\mathrm{offset,onshore,m}} \tag{28}$$

Table 6: Risk 1 Assessment methodology

Step number	Action	Variables	Timeline
Step 1	Calculate % of demand catered by RES source	$\%Solar_{demand}$	For each year from 2015-2018
		$\%Offshore_{demand}$	
		$\%Onshore_{demand}$	
Step 2	Calculate future % of RES contribution based on historical trend	(no extra variables created)	For each year from 2019-2043
Step 3	Obtain a reliable future % of RES contribution based on historical as well as future trends	(no extra variables created)	For each year from 2019-2043
Step 4 (= Step 3 – Step 2)	Calculate % of future RES contribution based on only future trends	$\alpha_{solar,m}$	For each year from 2019-2043 i.e. future year "m"
		$\beta_{offshore,m}$	
		$\gamma_{onshore,m}$	
Step 5	Calculate hourly correlation factor between RES and price	$\alpha_{solar,m-1}$for h = 1,…,24	For each year from 2015-2018 i.e. previous year "m-1"
		$\beta_{offshore,m-1}$ for h = 1,…,24	
		$\gamma_{onshore,m-1}$ for h = 1,…,24	
Step 6	Extract hourly MW RES-penetration	$SolarMW_{m-1}$ for h = 1,…,24	For each year from 2015-2043 i.e. previous year "m-1"
		$OffshoreMW_{m-1}$ for h = 1,…,24	
		$OnshoreMW_{m-1}$ for h = 1,…,24	
Step 7 (= Step 6 x Step 4)	Calculate future hourly MW change in RES-penetration	$\Delta SolarMW_m$ for h = 1,…,24	For each year from 2019-2043 i.e. future year "m
		$\Delta OffshoreMW_m$ for h = 1,…,24	
		$\Delta OnshoreMW_m$ for h = 1,…,24	
Step 8	Calculate hourly price offset caused by RES	$\alpha_{offset,solar,m}$	For each year from 2019-2043 i.e. future year "m
		$\beta_{offset,offshore,m}$	
		$\gamma_{offset,onshore,m}$	
Step 9	Use calculated hourly electricity price forecast based on only historical trend	$P_{,m}$	For each year from 2019-2043 i.e. future year "m
Step 10	Calculate new hourly electricity price forecast based using both historical and future trend	$P_{,m,new}$	For each year from 2019-2043 i.e. future year "m

The original forecasting in Chapter 3 assumes various different factors and those factors indirectly impact prices. To forecast the prices of 2019, it takes all of those factors over the period between 2015 and 2018 and creates an hourly correlation of the factors of each year. These factors are then used as an input to conduct a sensitivity analysis which aims at investigating if the forecasted prices will vary enough to not follow a normal distribution probability function. This risk analysis is based on the fact that everything that is produced is consumed, ignoring the line losses and other technical parameters. This assumption enables the calculation of how much of the demand was met by the penetration of solar PV (in MW), onshore wind (in MW) and offshore wind (in MW). Using linear regression, the future penetrations for each technology was calculated, for the years 2019 to 2043, based on only historical trend. This percentage of penetration encompasses solely the historical trend that was followed 2015-2018, that was also used to generate the initial set of forecasts that is used in answering sub-question 1. However, there are certain factors that do not necessarily follow historical trends. For instance, the initiatives by the Dutch government to reach the proposed clean energy targets is expected to bolster the growth of renewables at an exponential rate. This rate is expected to be higher than the one accounted for by the original model. Hence, there is a need to account for these future changes based on market factors, along with the historical impacts, in the sensitivity analysis, by referring to reliable reports. The price forecast for each year upon accommodating a combination of the change in the three energy sources mentioned before, was based on the year just preceding that. The forecasted penetration of these different renewable energy technologies, that includes future changes, was found from the confidential data given by PwC. The difference between the two values give a % penetration difference, thereby eliminating the historical impacts being accounted for twice. This was then multiplied by each corresponding hourly penetration by solar in 2018 to get a difference in penetration in 2019. This difference in penetration is multiplied with the correlation factors that was found earlier, to give a new set of correlations, specific to 2019. These new set of correlation factors were then added to the original 2019 forecasts to get the new prices based on fluctuations. The idea is that price will increase or decrease based on the new delta penetration, which was not accounted for in the original forecast as the original forecast was based on historical trends only.

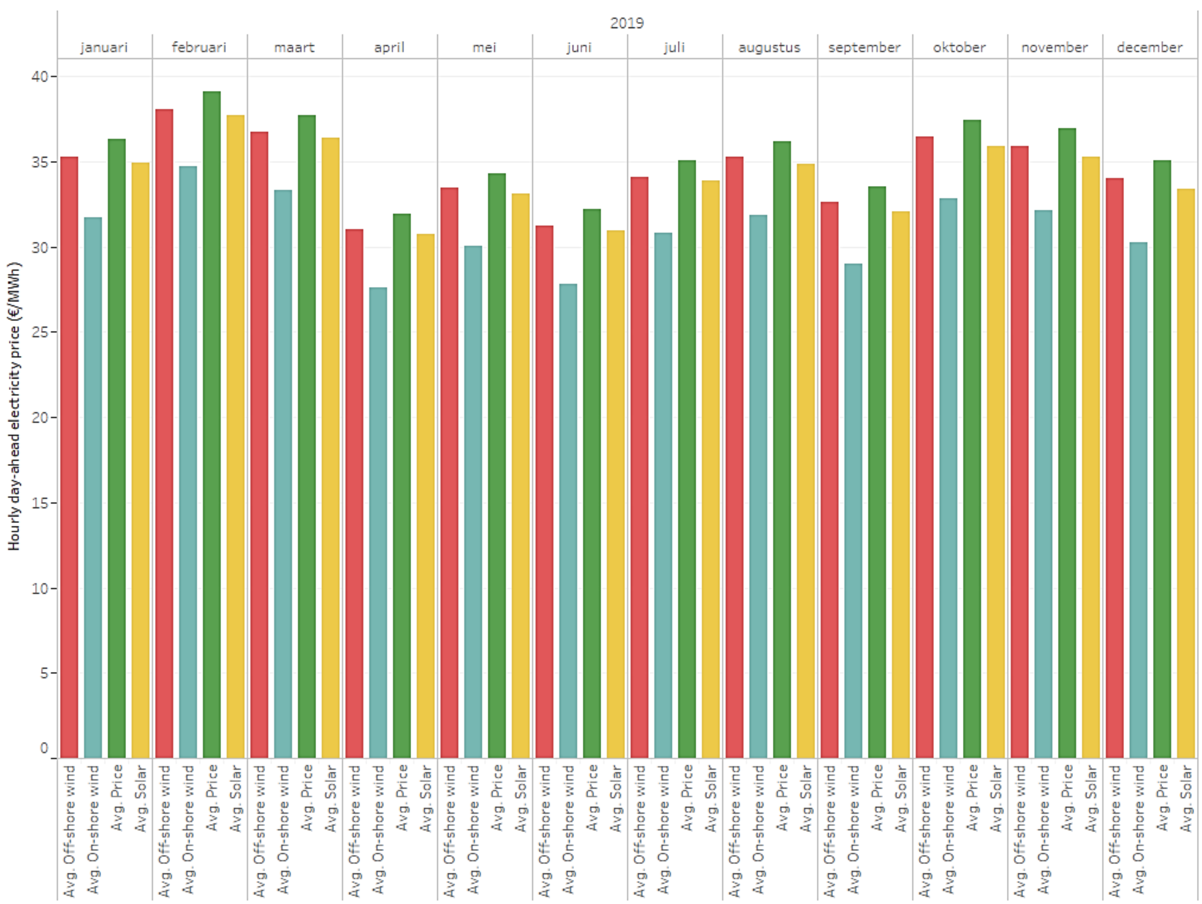

Figure 22: Relation between each RES affecting the price while the other two remain constant

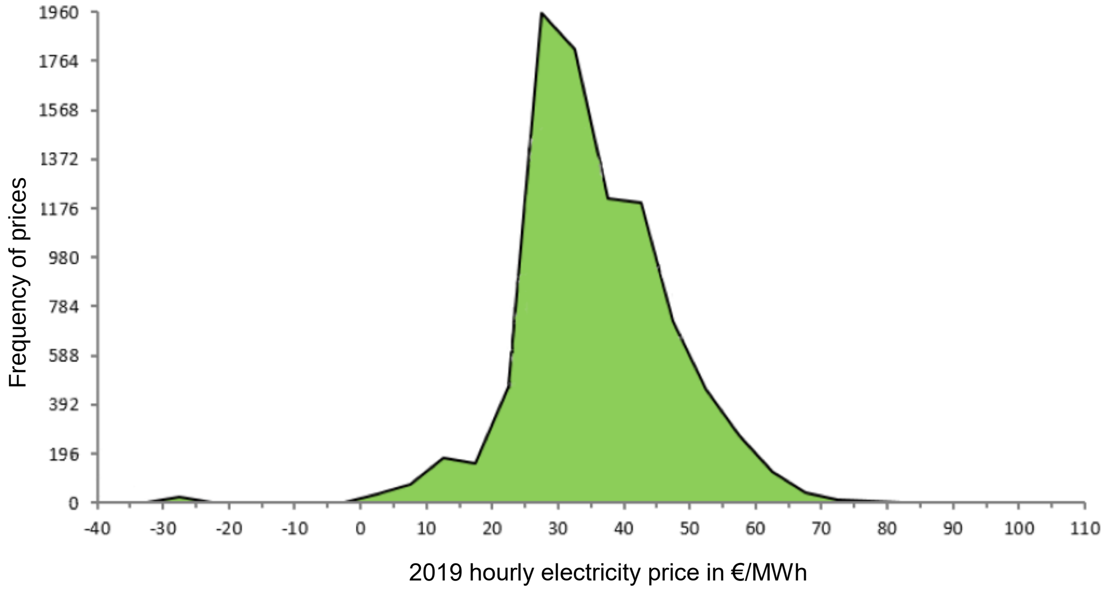

Figure 23: Hourly electricity price 2019 as a normal distribution

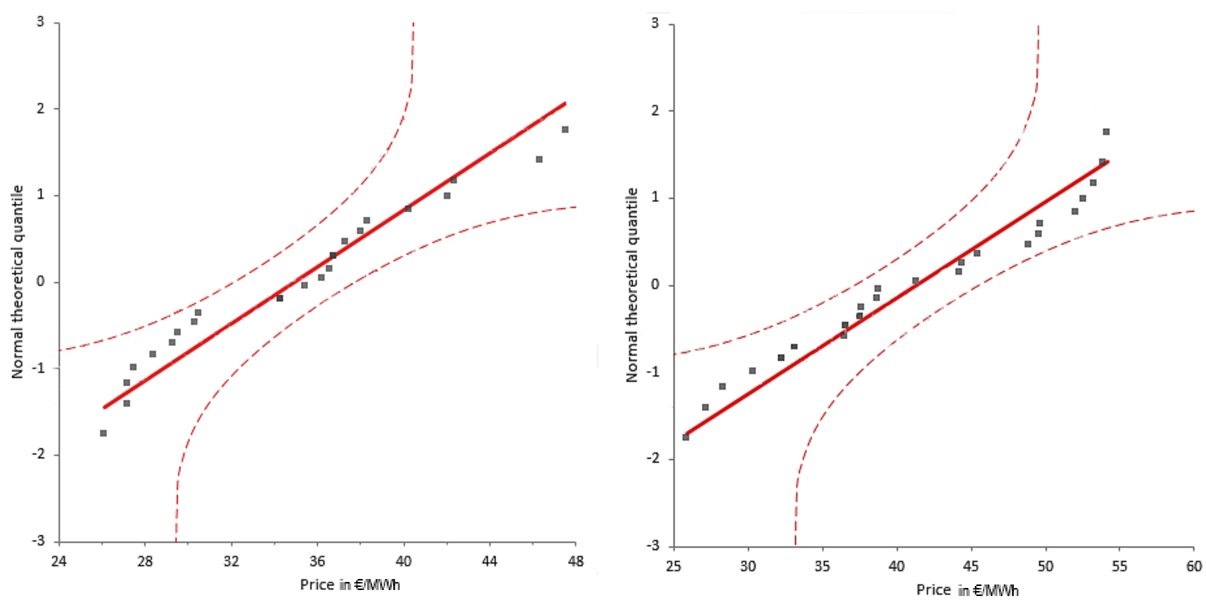

Figure 24: Two random days chosen for Q-Q plot representation; Left – 01.03.19; Right – 01.10.19

6.3 Risk 2: Non-normal distribution

Two facts were quantifiably confirmed at different points in this research. The first fact was that daily electricity prices tend to follow a normal distribution, while the second one was that there are exactly 4 points in the section below μ - 1σ and 4 points in the section above μ + 1σ. Both of these facts are key to the strategy, and hence the risk associated to the failure of these assumptions needs to be accounted for.

It is known that for normal distributions, about 68% of results will fall between +1 and -1 standard deviations from the mean. About 95% will fall between +2 σ and -2 σ. This is the basis of the strategy proposed in this thesis. However, it is also evident from the correlation matrix in Table 1 that there was a relatively higher correlation between offshore wind and the prices.

Figure *22* also portrays how each RES (for example, say off-shore wind) if the other two do not change (i.e. if solar and on-shore wind remain constant) will affect the hourly price over 2019. It is evident that a higher penetration of off-shore produced electricity will also make the price volatility very sensitive to changes in off-shore wind penetration, thereby resulting in a non-normal distribution of hourly prices.

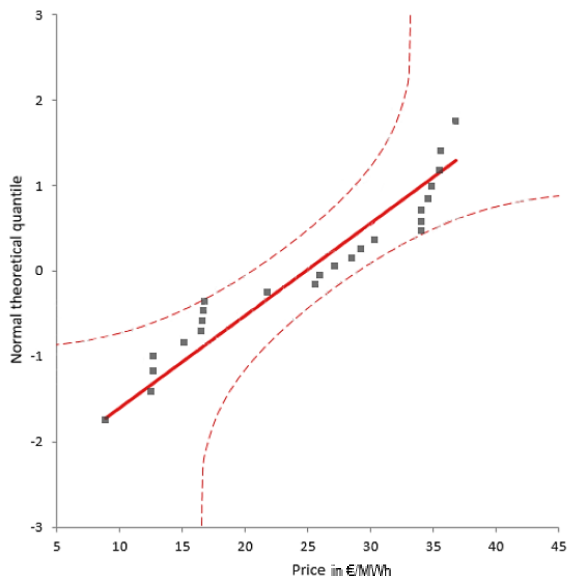

Figure 25: Anomaly - Non-normal distribution's Q-Q plot representation of 20.10.19

The Empirical Rule does not apply to all data sets, only to those that are bell-shaped, and even then is stated in terms of approximations. A result that applies to every data set is known as Chebychev's Theorem.The Chebychev Theorem allows you to evaluate percentages for any distribution, even if that distribution isn't normal [101]. It states that if k is a positive real number greater than 1, then minimum 1-$(\frac{1}{k^2})$ points of the data of a given sample fall within k standard deviations from the mean. The theorem presents the portion of the data which must at least lie within a certain standard deviations of the mean; the actual share of the data can be of a greater value [101]. There is no lower limit on the sample size, but statistics usually states that higher the sample size, more powerful will be the results.

A new strategy based on this theorem will explain the risk-assessed minimum number of hours that can be used to charge and discharge the BESS. The same methodology used to design the hedging strategy (as in Chapter 4) is used with the Chebychev theorem percentages instead of the empirical formula. This gives

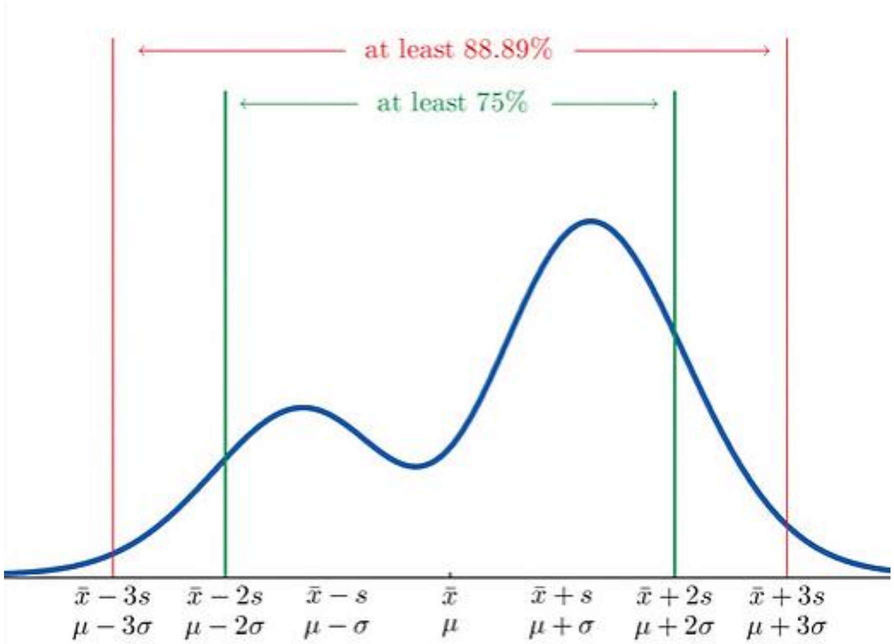

Figure 26: Probabilistic representation of Chebychev's Theorem *[101]*

3 hours of charging and 3 hours of discharging, in contrast to the 4 hours considered in the original hedging strategy, as seen in Table 7.

Table 7: Numerical test values for non-normal distribution

Standard Deviation intervals	Percentage under each interval	Number of points (out of 24) in each interval
Between - 3σ and - 2σ & + 3σ and + 2σ	25 %	≈ 6 points in total i.e. 3-hour battery
Beyond -3σ and + 3σ	1 %	≈ negligible

There is a business risk associated to there always being 4 distinct points less than -1 standard deviation and 4 distinct points greater than +1 standard deviation. If these 4 distinct points are not practically identifiable every day, the strategy is at risk. Since it was methodically found in Chapter 4 that installing the BESS at the intermediate-scale in the distribution grid will give the best returns, the 3-hour hedging strategy was applied at the same scale to see if there would be any change in the time to yield returns. An economic feasibility using NPV and IRR was conducted at that scale to quantify the business risk.

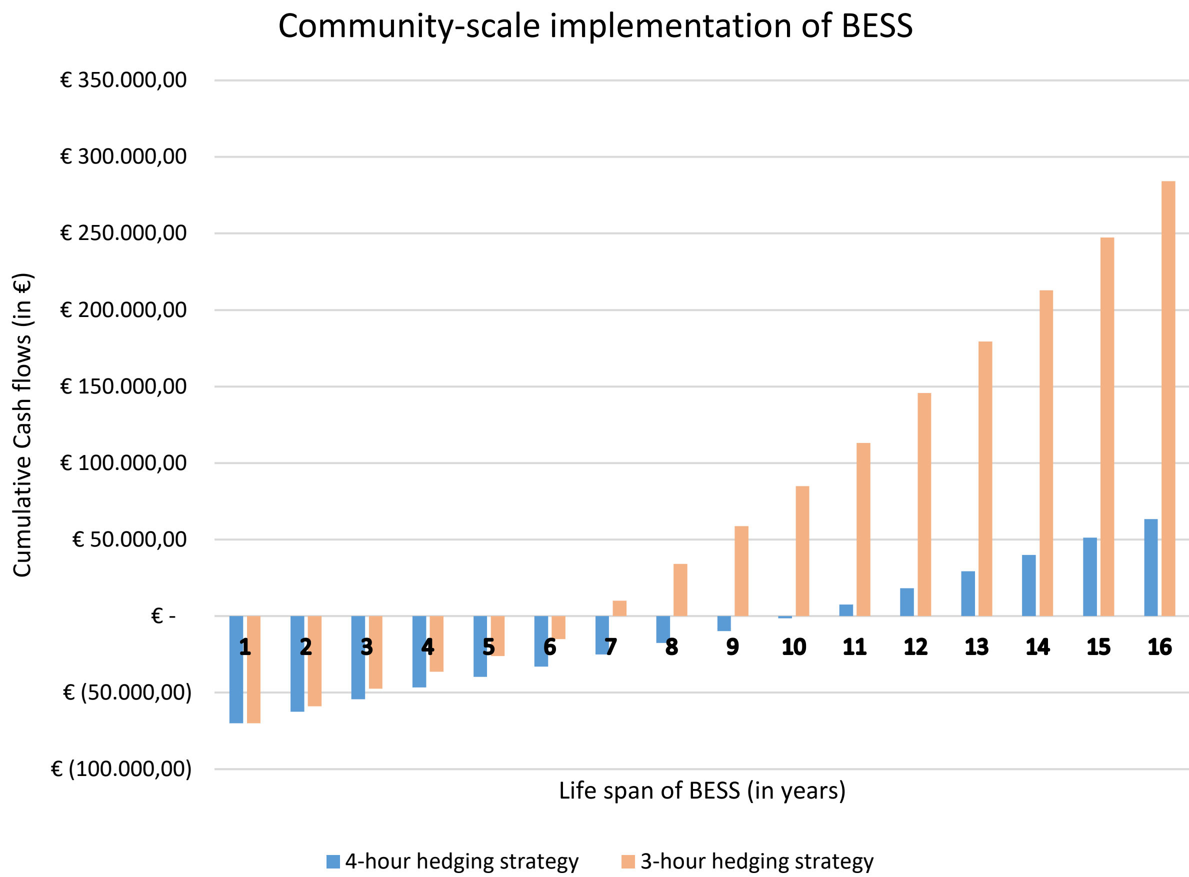

Figure 27: Business risk of Chebychev distribution at the intermediate-scale

As can be seen in Figure 27, the breakeven using a 3-hour hedge occurs somewhere from the 7th year in contrast to around 10 and a half years in the normal scenario of a 4-hour hedge. The strategy when at risk, also performs well and is proven to be more feasible than the original strategy.

It is crucial to understand hereafter that this is the worst-case scenario which depicts all the days of the 25 years offering an exchange of 6 hours of electricity instead of 8 hours. However, on scrutinizing the data in the forecasts for the next 25 years, it can be seen that the data is normally distributed. Therefore, though there will be days on which the Chebychev's distribution will be observed or there will be only 6 hours of interchange available, on the outset most days will have normally distributed electricity prices, and ensure the original strategy works. It is also necessary to note that not all risks are infeasible. Volatility itself is a major risk on many stakeholders but can be used to some other stakeholders' advantage. Even though the risk posed by the strategy is economically feasible, the energy suppliers cannot implement this as their main strategy. Main reason being the personal savings by the end user of the newly proposed strategy is relatively negligible compared to the savings posed by the originally proposed strategy. The consumer benefit in € is calculated in section 5.4 to incorporate into the NPV and IRR calculations. Just for the reader to gain perspective, the savings that consumers enjoy by accepting BESS embedded with logic served from both kinds of strategies is compared in Figure 28.

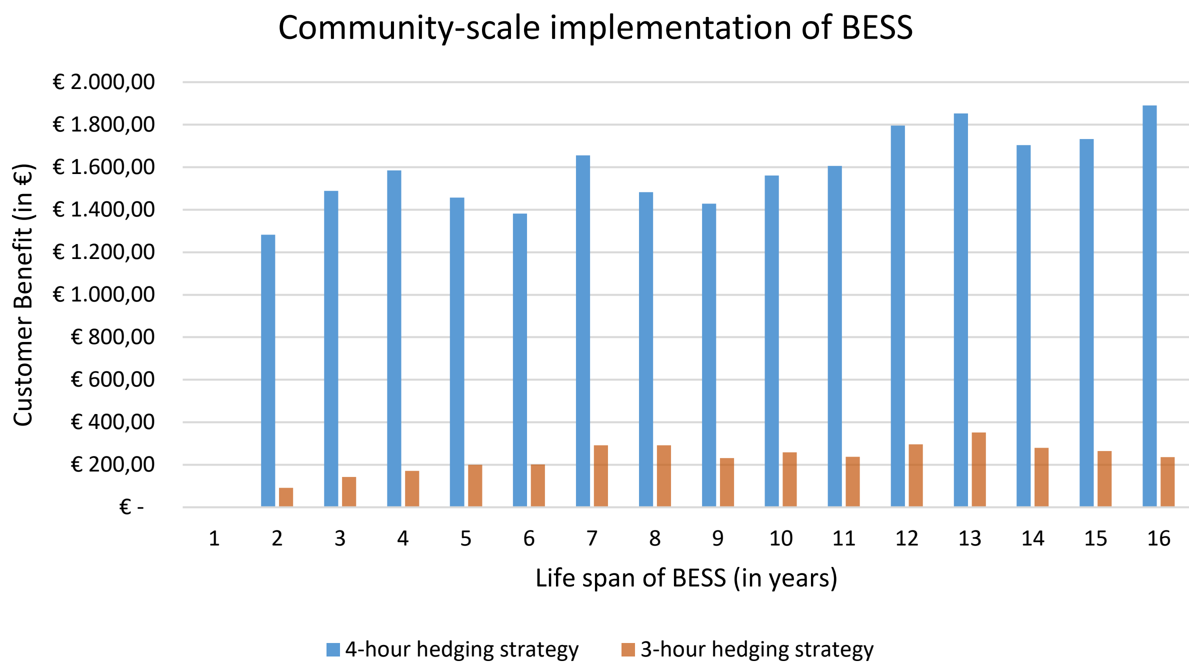

Figure 28: Comparison of consumer benefit (in €) upon the implementation of original hedging strategy (4-hour) and the risk-averse strategy (3-hour)

7

Conclusions & Recommendations

Past studies in the energy transition domain and the research presented in the previous chapters of this thesis report, have made it very evident that implementing RES on large scale at a sudden pace to meet various targets proposed by the Netherlands in various agreements holds the potential to compromise the reliability of the power grid, mainly due to the lack of controllability of these sources. This uncertainty posed by an increasing penetration of renewables in the grid has been found to make the electricity price more erratic, thereby increasing the electricity price volatility. Electricity price volatility is not a new aspect of the electricity market. In the past and even today, fluctuating coal and gas prices, increased competition in the markets and the inability to manage demand side uncertainty have created volatility. In the electricity infrastructure, like any industry, volatility poses unknown risks and the market participants hedge their risks via contractual agreements. However, these traditional hedging techniques are limited to a certain number of preset transactions and do not take into account the spike or drop in transactions that will follow variations in grid penetration due to renewables. It was concluded that current hedging techniques will have to be modernized or replaced by more dynamic forms of hedging to keep up with the unpredictability that RESs bring.

This provided an opportunity to develop one such dynamic hedging method based on energy storage to reduce the private entity's exposure to market price volatility.
ESSs (BESS, to be specific) is used to implement energy arbitrage for profitable hours in a day, thereby creating value out of electricity price volatility. This is the methodology used to design the hedging strategies proposed in this thesis. Along with hedging risks, it is necessary that a solution having the ability to provide versatile services be chosen. ESS, well-studied technology in the past decade, are known to be cost effective and aid a relatively smoother transition to a clean energy economy by providing enhanced system flexibility (either flexible generation or flexible demand) to maintain grid balance and by making RES more demand-driven. Since "flexibility" does not have a standard definition, it should be noted that it is defined

as the system ability to respond to uncertain generation and demand, while maintaining a constant balance between them to better manage the grid, for the purpose of this study.

The research conducted during this thesis has been aimed at answering one main question, which explains the motivation behind the hedging strategy and its contribution in reducing the price volatility faced by the private entity:

What hedging strategies using storage units at the distribution level, that enable price volatility mitigation in the coming 25 years, can be formulated?

In order to address this question and see how it was formulated, an analytical and heuristic approach is used, which consists of four main sub-questions, discussed in the section below.

7.1 Supporting research sub-questions

- **The first supporting research question is "What does the electricity market domain look like in the next 25 years (i.e. 2019-2043)"?**

  The main intention behind this sub-question is to determine the electricity price volatility that will exist in a day-ahead electricity market over the next 25 years. To answer this question, a statistical forecasting technique called ARIMA modelling is used to model the hourly electricity prices and forecast hourly electricity prices from 2019 to 2043. The day-ahead electricity market of the Netherlands (EPEX-Spot) is chosen for this research as it is found that the majority of the electricity is traded in the day-ahead market. For convenience, the future prices are forecasted mainly based on the trend in historical prices. The hourly historical prices of 2014-2018 are extracted from the ENTSO-E platform (an EU-owned database which is managed by the TSOs across the EU), which acted as the input to the ARIMA model. The output hourly prices are found to be extremely erratic, reaching up to 600€/MWh in 2041. The hourly electricity price between 2019 and 2043 is used to model the electricity price volatility of the future. It is found that the volatility had extremely high peaks in the future and the trend is only upwards, reaching up to 159€/MWh in 2041. Out of all the relevant energy sources affecting the price volatility, it is found that an increase in off-shore wind penetration created the most effect. The RES used to see the effect on volatility is shortlisted (out of solar, offshore wind, onshore wind, biomass, tidal, the first three were chosen) based on a report that provides the most contributing sources for the Netherlands to attain a 100% energy transition.

- **The second supporting research question is "Which hedging strategy purely based on electricity prices is the most economically feasible?"**

  An analytical approach, based on probability distribution function of hourly prices, is used to design the hedging strategy using storage units. While tackling this question, it is clear that the objective is to use electricity price volatility in the most profitable manner, while reducing the private entity's exposure to volatility. For this, it is necessary to have knowledge of the peaks and troughs in daily pricing that contributed to volatility. These peaks and troughs in prices are taken into account to carry out energy arbitrage, as energy arbitrage is found to be the revenue stream that created the most value while considering the value proposition of an ESS in the distribution grid. Further investigation of hourly spread of the day-ahead prices showed that majority of the 24-point intervals fit the Gaussian distribution, hence normal distribution is the selected probability distribution function. This provided an opportunity to use the empirical formula to assess the percentage of price points that fall within a bandwidth around the mean, with 68.27% of the values will lie within one standard deviation of the mean (taking the width from -1 σ to +1 σ) and 95.45% will lie within two (taking the width from -2 σ to +2 σ) and 99.73 will lie within three standard deviations (taking the width from +3 σ to -3 σ). The mean of the bell curve represented the most probable points, with the probability decreasing with each standard deviation, while standard deviation is the measure used to model daily electricity price volatility. Initial investigations showed that higher the volatility, higher is the probability of incurring profits. However, this would yield only 2.1% of the points in day to be profitable, which is equivalent to a 30-minute storage solution, depicting a non-marketable storage size. To utilize the entire potential of profiting from price volatility in a day-ahead market, a minimum discharging of 1 hour is necessary. Upon examination, it is concluded that the chosen ESS would have to charge at μ - σ and discharge at μ + σ to be an attractive investment, yielding a 4-hour battery. The results from answering this sub-question set a starting point to determine an economically feasible battery size.

- **The third supporting research question is "At what level in the grid and using which storage technology, can this hedging strategy be used?"**

  The minimum charging/discharging hours of the ESS found in the second research sub-question demonstrated the minimum size of the storage solution that could be used to implement this hedging strategy. Keeping that as the basis, several ESS are compared and stationary batteries (BESS) are found to be the most appropriate solution. Li-ion BESS is selected due to its rapidly lowering costs, extremely quick response time, high cycle efficiency of a minimum 89% and excellent charge retention property. Li-ion BESS is placed at three different levels in the distribution grid – large scale (megawatt level), intermediate scale (community level in charge of several households) and household level. In order to determine the placement position in the distribution grid that would yield the best business model, a break-even economic analysis, driven by NPV and IRR evaluations, are carried out. These financial figures confirmed that the hedging strategy using the BESS would make the most financial sense if implemented only at the community level. This decision is considered to be holistic one as it took into account the following factors for each year over the lifetime of 15 years:

  - Annual revenue in € (by accounting for the revenue made from the 4 most profitable price volatility points over a year)
  - Annual cost in € (by accounting for yearly O&M costs)
  - Annual cash flows in € (by factoring in yearly revenue, costs and a tax factor)
  - Cumulative cash flows in €
  - System efficiency in % (gives how much power is actually utilized after considering losses)
  - Tax factor (corporate tax, if applicable)
  - Power rating (in MW or kW, as this gives the maximum amount of power that can be drawn)
  - Residual value of the BESS in €, if applicable
  - A percentage of customer savings (i.e. consumer benefit in €) that the BESS owner can charge as service fee

  The BESS selected for installation at the community level is a Tesla Powerpack with a rated power of 52.5 kW and rated energy capacity of 210 kWh. A tax of 19% is taken into account as corporates in the Netherlands are obligated to pay 19% corporate tax if their profits are under €200,000 each year and 25% if above. In the future, when storage businesses are recognized as green, there is a possibility that the tax levied on them will be reduced or subsidized.

This research sub-question is answered under the pretext of the hedging strategy holding true. However, an unpredictability in electricity prices will prevent the probability distribution to be always normal, posing a risk for the private entity during strategy implementation, a solution for which has been provided in the next sub-question.

- **The fourth supporting research question is "What risks will the private entity, providing the services, be exposed to?"**

  This research question assessed the main risks that a failure in implementing the hedging strategy would pose. These risks crop out of two main reasons – a change in the renewables penetration due to changes in policies (which will result in the hourly prices not following a normal distribution) and due to unknown reasons when the hourly prices do not follow the normal distribution anyway. Since the physical strategy proposed is analytical, a mathematically formulated risk management is carried out for both the scenarios and it is found that, the hourly pattern of the daily price follow the Chebychev distribution, in the event that the patters do not follow a normal distribution. The Chebychev distribution provided new hedge-able 3 hours. A business risk, which is concluded to be feasible in investment is found when the new hedge-able 3 hours are used to see where in the distribution grid, the hedging strategy yielded the best results. The community level for BESS installation is still attractive to investors, showing returns around 3 years in advance.

7.2 Limitations & Future research scope

A few limitations of scope in this thesis, along with ways to extend the scope in the future, have been discussed below.

I. The research carried out in this thesis only offers insight into the impact of the BESS-based hedging strategy on two specific stakeholders in the distribution grid – an energy supplier and a local community. The upstream impact on the transmission grid capacity is not assessed here. Therefore, it cannot be claimed with absolute certainty that a physical storage hedging solution will maximize the overall grid quality. Hence, an assessment involving technical grid constraints, both at the distribution and transmission level, is important to gauge the complete effect of this solution.

II. Given the fast-changing technological diffusion in the energy industry, it is significant to study the effect that Artificial Intelligence (AI) and Blockchain can have on the implementation of this strategy. For example, using AI for long-term and short-term price predictions and using blockchain to manage the transactions of electricity between the BESS and the community can make this strategy more efficient and secure.

III. This study did not look at the effect of policy and regulations upon implementing this idea of hedging using storage units. The electricity market of the Netherlands is still not as flexible and accessible like that of the USA, hence the business model was designed in a way that the storage asset (or any asset) would be owned by an existing energy supplier. A detailed study of how the market design will have to change for a completely external new private entity that wants to act like an arbitrageur, will lead to the design of several other business models revolving around the proposed hedging strategies.

IV. Given the lack of access to data, the hedging strategy was designed mainly for the day-ahead market. A look at its application in the intra-day market for a hedging strategy closer to electricity delivery, holds an impressive prospect.

Apart from limitations in scope, a few limitations in methodologies and relevant improvements, have been

I. An intricate electricity price prediction model was not possible in the scope of this thesis given the time constrains, which is a limitation. This thesis did not intend to yield the most accurate results of price forecasting as that is a dedicated research in itself. The forecasts were just meant to support the design of the hedging strategy using storage units.

II. Rule of thumb of data analytics says that a 25-year prediction requires at least 12.5 years of historical data. However, the lack of provision to acquire data without having to make heavy payments or breaching privacy laws, affected the accuracy of the prediction. ENTSO-E reserves data only of the past 5 years, starting any point. This means, had data extraction begun in December 2018, only hourly electricity price data between 2014 December to 2018 December would be available. Had the data extraction begun in, say March 2019, this would reduce the accessibility of historical data. Since this thesis spread over 2018 to 2019, a delay in data extraction compromised the historical data that was finally available.

III. The proposed BESS-based hedging strategy was designed based on energy arbitrage using hourly electricity prices. The energy arbitrage did not take into account capacity constraints or any other technical constraints. For a more holistic impact of this strategy, a look into the technical aspects is important.

IV. The proposed BESS-based hedging strategy was a result of a completely analytical approach, using scenario analysis to determine the strategy is the most suitable. It used a sensitivity analysis for risk management and offered alternate solutions using other analytical, self-curated methods. Lack of scientific research in area of using probability distribution of hourly electricity prices for energy arbitrage, to hedge against risks, led to the utilization of a purely mathematical based approach. This lays a perfect ground to further carry out mathematical optimizations to answer important questions like what should the load demand of the community look like, should the community be only houses or can it be a mix of industrial and residential platforms, is there a possibility to first optimize the size of the battery using a combination of grid node constraints and the load at the nodes to see how many hours can be used to hedge using the strategy, and so on.

V. A main thing to note is that no matter how accurate a future forecast of prices is, the uncertainty of it changing is extremely high as future can never be predicted to a 100% accuracy. The probability distribution functions can also vary depending on the future prices, which means it may not always remain as a normal distribution. In this case, a Gaussian mixture or any other kind of probability distribution function can be applied In the event that the prices fall on a normal distribution curve, this strategy can be perfectly applied. Else, the researchers will have to use the same approach in a probability distribution function that is able to yield the percentage of points under each portion of the curve like the normal distribution does.

7.3 Brief critical analysis of the work carried out

From a theoretical standpoint, this study is perhaps a first attempt at proposing an analytical strategy to reduce a private entity's exposure to hourly electricity price volatility, while profiting from it, in a day-ahead electricity market. The private entity is considered to be a market participant in the distribution grid that is completely deregulated and aims at offering electricity that is not, for example, an energy supplier that does not own generation assets. The strategy employed by the private entity makes use of probability distribution of electricity prices. The strategy is the primary contribution of the work and can be applied across other probability distributions, with normal distribution being the easiest approach.

From a practical point of view, this work helps market participants or consulting companies that want to propose a business model for a market participant (private entity or an arbitrageur). It helps the consulting company understand if the private entity can implement a hedging strategy using a physical solution like the BESS, to survive in the event of extreme price volatility and take advantage of the volatility.

Apart from arbitrage using electricity prices and reducing the exposure to volatility, the storage asset would be of limited use if it would provide no other benefit at the distribution grid level. From a scientific point of view, this study provides the DSOs with an option to utilize the BESS for services like congestion management and as an avenue to avoid grid reinforcements. Congestion Management, with the help of the BESS mentioned in this thesis, can be used to prevent the overloading of grid assets. The physical hedging strategy provides DSOs with a solution to defer the payments they would make towards laying new grid lines as a means to upgrade the distribution grid. By storing electricity and releasing it at a favourable time, BESS can help in grid overloading, increasing the efficiency at which grid capacity is used and avoid investment in early asset replacement.

By looking at different standpoints, the work carried out in this thesis can adapt to provide a solution for issues cropping up in a wide range – from electricity markets to aiding DSOs to reduce costs in grid reinforcements.

If given the chance to approach the price volatility issue in another manner, the analytical approach would still remain as the first choice given the ease with which it can be applied even by stakeholders possessing very little knowledge about the technical aspects of the electricity infrastructure. However, a higher importance would have been put on the forecasting methodology i.e. either by finding ways to obtain a pre-existing electricity forecast or devoting more time for hourly price prediction. The former is mentioned because the possession of existing forecasts would have paved way to focus on optimizing the strategy by carrying out mathematical optimizations. While the latter has been mentioned because the accuracy of the price forecast definitely directly affects the accuracy of the strategy designed. This study considers a well-known and basic tool to forecast prices that requires only the historical trend, but more complex models that take into account other factors are possible.

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