Louvain School of Management
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Impacts of day-ahead power market conditions on flexible grid-connected water electrolysis in Europe

A Levelized Cost of Hydrogen analysis

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Executive Summary

Water electrolysis is a promising technology to decarbonise hydrogen production. The European union is planning its integration to achieve ambitious climate goals. However, electrolysis costs need to decrease to be implemented at a large scale. A solution pointed out in the literature is the participation of water electrolysis facilities as a demand-side management tool. By optimizing day-ahead biddings, electrolysers could become competitive with other hydrogen production technologies. This master's thesis contributes to the scientific knowledge through three objectives. In a first place, it aims to give a broad picture of the European day-ahead market landscape. To do so, eight European market areas are investigated (Belgium, France, Germany the Netherlands, Northern Italy, Southern Norway, Spain, and Western Denmark). Secondly, this master's thesis evaluates the impact of day-ahead market conditions on flexible water electrolysis through an alternative definition of the Levelized Cost of Hydrogen in Europe. To achieve that, four price scenarios for future day-ahead markets based on historical data are built and applied Alkaline and Polymer Electrolyte Membranes Electrolysis. In total, three historical years (2017, 2020, and 2021) and three bidding areas (Belgium, Western Denmark, and Southern Norway) are selected. Lastly, this document evaluates the impact of using Auto-Regressive Integrated Moving Average day-ahead price forecasts on the Levelized Cost of Hydrogen. It is demonstrated that low prices as well as high capacity factor of the electrolysers are necessary to reach higher profitability. Simultaneously, at comparable mean day-ahead price levels, high volatility improves the water electrolyser's profitability. Polymer Electrolyte Membranes Electrolysis is also demonstrated to be the most cost-efficient technology. Finally, ARIMA price forecasts do not significantly affect the Levelized Cost of Hydrogen.

Contents

1 Introduction

Following Intergovernmental Panel on Climate Change recommendations, European Union has committed to reducing its greenhouse gas emissions by 50% by 2030 to limit global warming by 1.5°C [16; 33]. Nowadays, hydrogen production, crucial for the ammonia and petrochemical industries, still relies upon 96% on fossil fuels [67]. To cope with the ambitious climate goals, the sector has to be decarbonated. One technology is considered to play an important role in this transition: water electrolysis [42]. This process, converting power into hydrogen, has drawn the attention of many governments and scientists in the past years. Indeed, due to the responsive feature of electrolysis, the potential of this technology could go much beyond the decarbonisation of hydrogen production. By either acting as a grid service provider or as power storage mean, water electrolysis could help the European Union to reduce its dependency on fossil fuels, still accounting for 43.9% of the power and heat generation [14].

Even though water electrolysis displays many promising applications, this technology is not seen yet as profitable. The investment and operating costs make it still non-competitive with other power storage solutions and hydrogen production technologies [59; 66]. Nevertheless, while [59; 66] consider a fixed amount of Operation and Maintenance Expenses, thanks to their fast-responsiveness, water electrolysis facilities can act as a demand-side management tool. Their power bills can therefore be reduced by optimising their power consumption schedule on the day-ahead market to avoid peak hours [19]. This dimension has been less explored in the literature [34; 46; 47; 50; 62].

Moreover, due to the complexity of the modeled facilities and the specificities of each power market, many studies only consider one market area at the time [3; 11; 34; 42; 27; 47; 60]. Comparing results from different studies is not relevant as different assumptions, business models, technologies, and market designs are assessed. Yet, a clear vision of the profitability of flexible water electrolysis is necessary to foster the energy transition. This master's thesis thus aims to help water electrolysis market participants by giving them insights into how day-ahead market conditions impacts flexible water electrolysis facilities' profitability in Europe.

The European power market is composed of several different bidding zones. Among these zones, day-ahead electricity prices can differ widely and an individual assessment is therefore necessary. However, to keep the scope of this master's thesis realistic, a limited number of market areas must be studied. To select the bidding zones, a statistical comparison of eight bidding zones is performed. I choose the initial set of market areas to be as representative as possible of the European power markets. The statistical study focuses on the mean, the dispersion, the outliers, the correlation, and the variability of the day-ahead prices. Of the eight studied market areas, Belgium, Western Denmark, and Southern Norway are chosen as they display significant different combinations of mean day-head price and variability while showing potential for the development of water electrolysis facilities. From the analysis, four price scenarios based on 2017, 2020, and 2021 day-ahead prices are also built to evaluate potential future market conditions.

To evaluate and compare electrolysis' profitability, the Levelized Cost of Hydrogen is commonly used as a metric in the literature. This metric is defined as the break-even hydrogen value [€/kgH_2] to cover the lifetime costs [37]. An evaluation of the Levelized Cost of Hydrogen can be made by actualising the investment costs and computing the operational expenses, including electricity consumption [50]. By modeling and simulating the economic activity of a water electrolysis facility under the different price scenarios, determining what market conditions make water electrolysis the most profitable is possible. Sensitivity analyses are also performed to estimate the impact of each parameter on the Levelized Cost of Hydrogen. In practice, the business case of a flexible grid-connected electrolyser with a storage facility supplying a fixed demand is considered. The hydrogen producer can forecast day-ahead power prices to optimise its power consumption schedule.

The master's thesis shows that both, low prices and high variability, can positively influence the Levelized Cost of Hydrogen for both technologies. A sufficient number of operating hours is also necessary to optimise the cost dimension. Furthermore, Polymer Electrolyte Membranes Electrolysis is demonstrated to be more profitable than Alkaline Electrolysis. Finally, the utilisation of forecasts in my model does not influence significantly the Levelized Cost of Hydrogen.

The master's thesis is organised into eight main sections to answer the research question.

The methodology of this master's thesis is first explained. Then, it is followed by a review of the background and the literature to understand the different stakes. Afterward, day-ahead data analysis is performed to highlight price differences in Europe and build price scenarios. Based on these scenarios, forecasting simulations are performed. A case study is then described. Next, the bidding strategy of the case study is modeled and explained. Results are finally computed for the three selected market areas under the different price scenarios. Limits of the analysis are later described before concluding.

2 Methodology

The first part of the master's thesis consists of a theoretical approach. A background analysis is performed to identify state-of-the-art topics and to set up the framework of the problem. I then investigate the development of water electrolysis in Europe. European power markets are then briefly described to understand their interactions with the electrolysis process. Furthermore, I review the literature to assess the potential profitability of every business model, to evaluate synergies between with demand-side flexibility and to investigate the existing techno-economic analyses of electrolysis.

In the next section, I analyse the historical day-ahead power price data of several European bidding zones. The goal of this section is to properly understand the differences in the price structure of each zone. I first take a global approach by comparing eight different market areas before limiting the scope to three. The main decision criteria are based on the price levels and the price volatility as they are the key factors of electrolysis' profitability. Yet, other metrics, i.e. median, correlation, number of negative price periods, and dispersion are also used to differentiate the bidding zones. After investigating, Belgium, Western Denmark, and Southern Norway remain as the most appealing areas with the most significant differences in their price profiles for water electrolysis. By analysing these three zones, the thesis aims to provide the broadest view possible of the European power landscape while keeping a reasonable scope. I also built price scenarios based on historical data. The objective is to set different trajectories that power prices could take in the future. I use these scenarios to assess the model's profitability. The data have been collected from the ENTSO-E Transparency platform. Throughout the whole analysis and modeling, I use the software R-Studio.

In the next step, I add an electricity price forecasting dimension. Flexible facilities rely on forecasts to optimise their day-ahead biddings. I apply a four-step methodology from [8] to fit an ARIMA model and to forecast day-ahead prices. The forecasts are then used in the case study to assess the process profitability.

Furthermore, I model a case study to assess the profitability of water electrolysis. I define its scope based on the literature review performed in the previous sections. Most of the techno-economic analyses use the Levelized Cost of Hydrogen (LCOH) as a metric [34; 20; 62]. The latter uses the following formula corresponds to the Net Present Value of the future costs and hydrogen production:

$$LCOH = \frac{\sum_{y=0}^{n} \frac{Costs_y}{(1+r)^y}}{\sum_{y=0}^{n} \frac{Prod\ H2_y}{(1+r)^y}} \tag{1}$$

where y is the year, n the lifespan of the facility, $Costs_y$ the overall costs undergone in year y, r the discount rate and $Prod\ H2_y$ the hydrogen [kg] produced in year y. The $Costs_y$ are split in two main categories: the Capital Expenditures (CAPEX) and the Operational Expenditures (OPEX).

However, due to nowadays power market conditions and the important uncertainty placed on future electricity prices [66], this master's thesis takes another approach. The Levelized Cost of Hydrogen is estimated under different power market conditions, to emphasise the impact of its main cost driver: electricity. Price scenarios should then be derived from it. The mathematical definition is reworked as [26; 48; 50]:

$$LCOH = \frac{CAPEX * \frac{r*(1+r)^n}{(1+r)^n-1} + OPEX_{fix} + OPEX_{var}}{Annual\ Hydrogen\ Production} \tag{2}$$

where r is the rate of return, n the lifespan of the facility (years), $OPEX_{\text{fix}}$ the fixed annual OPEX and $OPEX_{\text{var}}$ the variable annual OPEX.

In equation 2, the different components of the $CAPEX$ and the $OPEX_{fix}$ are described and estimated thanks to a literature review. On the opposite, the $OPEX_{var}$, constituted of power costs, can be computed through an algorithm simulating day-ahead biddings, as its value depends on the market conditions. This algorithm, its assumptions, and its constraints are characterised and justified in detail.

Thereafter, in the results section, I compute the Levelized Cost of Hydrogen for every price scenario built in the data analysis section. I assess and compare the impacts of market conditions for the two water electrolysis technologies. Furthermore, I measure the influence of day-ahead price forecasts on the Levelized Cost of Hydrogen. Finally, I perform sensitivity analyses to estimate the effect of key input parameters on the profitability metric. This master's thesis finishes by a discussion on the limitations of the analysis and by conclusions drawn to answer the research question.

3 Background

3.1 Water electrolysis technologies

Even though water electrolysis, also referred as the generic name of Power-to-Gas, has been considered only recently a credible way to reach European Union's climate commitment, this chemical process has been mastered for a long time. The first developments were done by Nicholson and Carlisle in 1800 [36]. Into the water, hydrogen is split up from the oxygen by an electric current. Oxygen can then be released into the atmosphere or collected for other uses while hydrogen is used as an energy carrier. The input power can be injected in two different ways: a centralised or a decentralised design. In a centralised design, the facility is directly connected to a renewable power station, i.e. hydro, wind, or solar, resulting in hydrogen with a very low carbon intensity. The latter is called "Renewable Hydrogen" or "Clean Hydrogen" by the European Commission. On the other hand, in a decentralised design, or grid-connected, the Power-to-Gas facility is directly connected to the grid as any other industrial power consumer. Its production is then designated as "Electricity-based Hydrogen". A decentralised design can also lead to "Renewable Hydrogen" if the generation mix has a low carbon intensity or if electricity has been purchased through a renewable electricity supplier utilising European Guarantees of Origin [17].

Thanks to its simplicity, this process has been rapidly industrialised. In 1902, 400 industrial water electrolysers were already deployed [36]. Over the years, the technology has evolved with investments in research and development. Three technologies are currently developed: Alkaline Electrolysis, Polymer Electrolyte Membranes, and Solid Oxide Electrolysis. Alkaline Electrolysis represents the most mature and is currently the cheapest technology benefiting from a longer lifespan. However, in terms of flexible operations, the development of Polymer Electrolyte Membranes is promising, reducing start-up times to a few minutes maximum. Theoretically, the operational load range of this type of electrolysis is located between 0% and 100%. In the opposite way, Alkaline Electrolysis can only decrease its load to 20% before completely shutting down and then requiring minutes to hours to go back to a production state [68]. Solid Oxide Electrolysis, on its side, is only at the development state and is promising in terms of efficiency but not suited to fluctuating operations [25].

Nowadays, electrolysis is considered a full-fledged tool by many governments to foster the energy transition. Its development is thus skyrocketing. Europe is leading in the area, representing 85% of the worldwide electrolyser's capacity. At the forefront of European countries, Germany is, on its own, representing 23% of this capacity [22]. Targets are clear for the European Union: reaching 6 GW and 40 GW of renewable hydrogen electrolysers respectively in 2024 and 2030. With such strong signals, investments are following the trend. The European Union expects €180 to 470 billion of cumulative investment by 2050. Projects such as Refhyne II in Germany tenfold the actual maximum capacity to 100MW and clearly proves the intentions of the market [39]. However, even if the goals are ambitious, the road to achieving carbon neutrality is still. Forecasts show that the actual installed capacity will be around 2.7 GW in 2025 in Europe. This figure is fifty times bigger than the installed capacity of 10 years ago, but it is still far from the original objectives [55]. To be a proper energy transformer and achieve the intended objectives, electrolysis has to be highly efficient, flexible, and cheap [36]. The profitability, compared to other hydrogen production and storage technologies, remains the biggest barrier to this promising technology [59].

3.2 European power markets

Electricity purchase represents one of the main cost drivers for Power-to-Gas [37]. Understanding the design and the interactions of power markets with electrolyser is, therefore, essential. In this section, a quick description of the different power markets is thus made to describe the different mechanisms taking place at the Transmission level within the ENTSO-E framework for an industrial power consumer such as an electrolysis facility.

3.2.1 Actual market design

In the framework of industrial power consumers such as an electrolysis facility, this section describes the different market mechanisms taking place at the Transmission level within the ENTSO-E framework.

The ENTSO-E area, responsible for the proper functioning of European power markets [43], is divided into five synchronous areas where the grid frequency should be equal. These synchronous areas are subdivided into several Load Frequency Control blocks which often correspond to the geographical borders. To maintain grid frequency and avoid a potential system collapse, electricity must be generated and consumed at the same time. Large-scale storage being currently impossible with electricity, it represents the biggest challenge of the power system. The balancing responsibility, i.e. monitoring the equivalence between generation and consumption, is assumed, within a Load Frequency Control block, by one or several Transmission System Operators. This responsibility is partially transferred to the Balancing Responsible Parties, representing a large group of generators or consumers. The Balance Responsible Parties are accountable for submitting balanced nominations before each delivery day. To avoid imbalance and to provide market participants with as much flexibility as possible, power markets have been organised in a time-sequential way from years to minutes before the delivery. The market zones, referred as bidding zones, are often similar to the Load Frequency Control borders. However, some Load Frequency Control blocks, such as Norway, Denmark, or Italy, use several bidding zones within their borders due to different transmission capacities [2; 38].

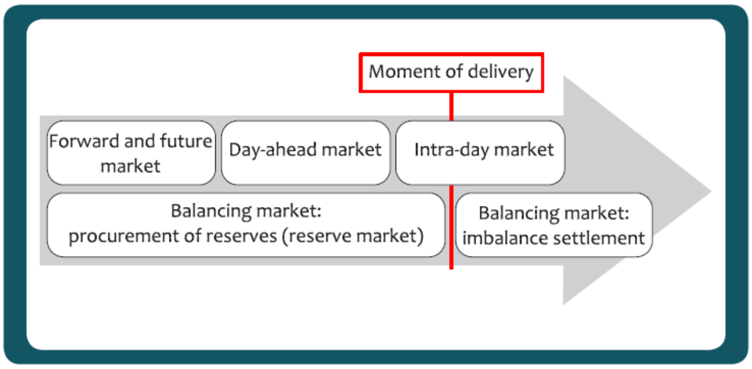

Figure 1: Electricity markets sequential order [38] (*p. 5*)

3.2.1.1 Forward and future markets

With exchanges that can take place years before the delivery, the forward markets have the longest time scale for power exchanges. These contracts are used by generators and consumers to reduce their respective risks related to power selling/buying prices and to ensure a minimum level of production/consumption.

3.2.1.2 Day-ahead markets

Representing the reference market for electricity in terms of volume traded, day-ahead markets allow power exchanges a day before the actual delivery at the Gate Closure Time, at 12:00 CET. Once the gates are closed, a single hourly clearing price, based on the Merit-Order, is determined for each hour of the delivery day [43]. The Merit-Order is determined by the match between the cheapest electricity supply activated and the demand. Only the bids under or equal to the clearing price are then activated. This system ensures a cost-optimal activation of generation means [2]. *Figure 2* summarises this process.

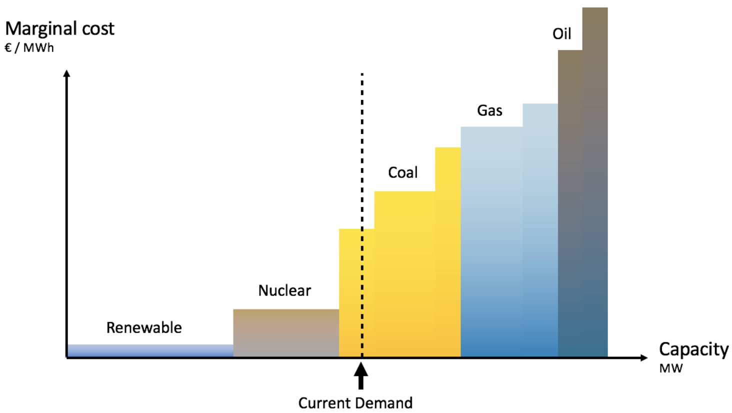

Figure 2: Merit Order Curve [9]

3.2.1.3 Intraday markets

To allow generators and consumers to adapt their nominations to the latest information and forecasts, intraday markets have been implemented. Deviations indeed often occur due to failure or changes in weather conditions. This market allows power exchange until one hour to 5 minutes before the actual delivery. The "pay-as-bid" principle is used. On the opposite to the day-ahead market, there is no single market-clearing price. The supply and demand curves are rather continuously evaluated as the stock exchange model [2].

3.2.1.4 Imbalance settlement

Whereas day-ahead and intraday markets are rather similar in European countries, the design of the different imbalance mechanisms widely differs and is currently an ongoing research topic. The final objective is to harmonise the different practices through the Network Code on Electricity Balancing [28]. After the delivery, an imbalance price is determined by the Transmission System Operator depending on the imbalance level of a bidding zone. If a Balance Responsible Party has deviated from its nominations, it must then pay this Imbalance price for each MWh deviated. Apart of this common feature, different market designs, regulations, and data availability are applied by the different Transmission System Operators making a potential comparison extremely complicated [28; 65].

3.2.1.5 Ancillary services

While the four first mechanisms rely on a voluntary reaction based on price signals, the ancillary services, or reserves market, happen when a market participant enters into contract with the Transmission System Operators to keep some capacity at a specified time and volume. Different types of reserves exist differing by their activation time: Primary Reserves, Secondary Reserves, and Tertiary Reserves [2; 38].

3.3 Water electrolysis profitability

Given the expected development of water electrolysis, researchers have started investigating this technology. However, several business models for electrolysers exist and their profitability varies with it. Power-to-Gas can either be used as power storage mean, as tool to maintain the grid frequency ,or as process to produce hydrogen.

3.3.1 Power storage

With the expected increase of the Variable Renewable Energy Sources share in the energy mix and the ongoing electrification, storage will have a key role in the future power systems [5]. Yet, only the most reliable and cost-effective technologies will be implemented [67]. Power-to-Gas will compete with three other technologies: electric batteries, Compressed Air Energy Storage, and Pumped Hydro Storage. Storage, in the literature, is often referred as time flexibility [42]. Consuming electricity when there is a surplus of power in the system, storing it as hydrogen in tanks or underground caverns, and restoring it through a gas turbine when the market is tight could make economical sense. Moreover, integrating more Variable Renewable Energy Sources in the system will increase the power price volatility [42], making time flexibility potentially more profitable. In addition, with relatively low energy losses over time, chemical storage may be particularly suited to seasonal storage whereas batteries and Pumped Hydro Storage[1] fail in this domain [31; 53].

Several studies have therefore analysed the potential of this application from a time flexibility perspective. It has been demonstrated that, for Sweden, the number of low price periods is still not sufficient to make the investments worth it [34]. Turning a Power-to-Gas facility into a storage facility indeed induces supplementary investments (i.e. compressor, gas turbine, etc.) [66]. In Denmark, [1] states that costs from repowering hydrogen should be 70% lower to be economically viable. In Italy, strong economical barriers also appear when the different storage technologies are compared from a Levelized Cost of Storage perspective. Compared to its competitors, water electrolysis suffers from higher CAPEX and OPEX. The biggest barrier is the very low efficiency when the hydrogen is reconverted to electricity. Overall, about 60% of the energy potential is lost [59]. Moreover, even though electrolysers are suitable for seasonal storage, daily capacities are expected to be the most demanded capacities [5]. Nevertheless, other storage technologies also have some drawbacks. Batteries require huge raw material requirements and have a strong environmental impact in terms of recycling, water consumption, and CO2 emissions. The geographical availability of Pumped Hydro Storage and Compressed Air Energy Storage is also limited.

In a 100% Renewable Energy Sources scenario, from which we are still far, Power-to-Gas is expected to play a role in the energy transition as storage mean [5]. However, storage should not be seen as the main business model for water electrolysis given the current cost levels and market conditions.

3.3.2 Grid services provider

Frequency deviations, happening when there is a mismatch between the power generation and consumption, are also bounded to increase. To tackle this problem, market participants provide Ancillary Services to the Transmission System Operators. From a technical perspective, the latest electrolysis technologies (Polymer Electrolyte Membranes and Solid Oxide Electrol-

[1]Traditional Pumped Hydro-Storage have daily to monthly storage cycles. This technology can also be suited to seasonal storage but needs specific installations, a major reservoir built in parallel with a major river. This installation is called Seasonal Pumped Hydro Storage and is less common than the original version.

ysis) are suitable for these services due to their high responsiveness [56]. The literature has also addressed this topic by studying participation in Ancillary Services in different European countries. In France, it has been shown that under 2015 market conditions, it was not profitable for electrolysers to participate in Frequency Control Reserves [27]. In Belgium, for a Chlor-Alkali Electrolyser, combining participation in the day-ahead market and providing Frequency Control Reserves is considered beneficial compared to constant load operations [3]. [60] confirms this result for Polymer Electrolyte Membranes technology.

However, overall, in most of the studies, participation in Ancillary Services is not done alone but combined with day-ahead nominations. It confirms the literature review performed by [56] where the authors conclude that grid stabilisation should not be seen as a final business model but rather as complementary revenues. Grid services indeed only represent 2-3% of the wholesale market turnover and therefore only basing operations on this part of the market would make no sense. [45] confirms that the Ancillary services do not account for an important share of the revenues and that end-use flexibility should be considered as the main income sources because the highest spreads are observed between the power spot market and the hydrogen market.

3.3.3 End-use flexibility

The last possibility for water electrolysis businesses to valorise their activity is to sell their produced hydrogen rather than reconverting it to electricity. This application would allow other highly carbon-intensive sectors such as transportation, industries, ammonia, and petrochemical productions to be decarbonated. Hydrogen production is still dominated at 96% by hydrocarbon-based technologies, decarbonating it is, therefore, essential [67]. Hydrogen can also be partially re-injected directly into the gas grid or turned into methane through biomethanation. All these solutions are referred as end-use flexibility in the literature [42]. Several studies have demonstrated that this application is more profitable than hydrogen storage [11; 56; 66]. However, compared to its competitors, Steam Methane Reforming with and without Carbon Capture, Utilisation and Storage technology, electrolysis still lacks economical efficiency. Its production costs are indeed higher [59]. However, improvements are expected to turn the business model more profitable. With the ongoing research and development, investment costs for both Polymer Electrolyte Membranes and Alkaline Electrolysis are expected to drop and their efficiencies to increase[66]. Together, with these technological improvements, a higher hydrogen selling price would also enhance Power-to-Gas' profitability. This change is considered as 'likely' as production costs from Steam Methane Reforming with and without Carbon Capture Utilisation and Storage, currently determining hydrogen market prices, are expected to rise due to higher methane and carbon prices [66].

To sum up, it can be concluded that end-use flexibility represents the best opportunity for water-electrolysis. Reconverting hydrogen into electricity in case of high power price variability and using as a grid services provider should then be seen as complementary activities.

3.4 Demand-side flexibility

Even though improvements are expected from both the technological aspects and from the hydrogen selling price, the power consumption will still represent a major cost dimension [39]. Furthermore, predicting long-term future electricity prices is extremely difficult. On the one hand, prices could drop due to more important market penetration of cheap renewable energy such as wind and solar. The latter will thus fix the prices, through the Merit-Order design, in more periods. This situation could be even more exacerbated by based-load power plants (coal and nuclear) suffering from huge start-up and shut-down costs and being therefore ready to pay negative power prices to avoid them [66].
On the other hand, coal and nuclear power plant phase-outs have started in many countries. The latter still accounts for an important part of their generation mix and therefore, in tight periods, more expensive generation means would be called to fulfill the demand. Furthermore, with the development of demand-side response technologies, the competition to access low price periods will increase [66]. However, this impact is considered "fairly modest" in the dutch power market [42].

Therefore, as the future of electricity prices is uncertain, reducing the power bill amount is necessary for water electrolysis. To achieve it, demand-side flexibility, or demand-side management, represents a good opportunity. Rather than following the conventional supply-follows-demand, markets are now designed so participants can adapt their production/consumption profiles to price incentives [2; 19]. Several interactions are possible [19]. The most important is the day-ahead optimisation. The price differences between day-ahead and intraday markets are indeed not sufficient to justify complex optimisation problems [66]. Furthermore, self-balancing, implemented by the Imbalance Settlement mechanisms, is difficult to compare between several countries due to the important differences in market designs, regulations, and data availability [28; 65]. Moreover, Balancing Reserves are onl considered as additional revenues for Power-to-Gas [56]. On the other hand, day-ahead markets represent the main part of the power exchanges [56] and their designs are similar in different European countries. A comparison between European bidding zones is therefore relevant.

Yet, only a substantial part of the literature tackles the impact of optimising day-ahead biddings on profitability. [46] offers the first insights to compare European bidding zones (France, Germany, and Spain), investigates, and proves the positive influence of avoiding peak hours on the Alkaline Electrolysis' profitability. [50] extends and precise the comparison between Germany, California, and Ontario by adding a storage facility to the model and detailing more components of both the CAPEX and the OPEX. Hydrogen storage acts as a buffer and allows Power-to-Gas to optimise real-time participation in the wholesale market. [50] proves that, with a seven-day demand hydrogen storage capacity, corresponding to an underground storage facility, both Alkaline and Polymer Electrolyte Membranes Electrolysis can compete with Steam Methane Reforming with Carbon Capture and Storage technologies. [23; 34; 66] emphasise the importance of having a sufficient number of operating hours to cover investment expenses and low electricity costs. [62] corroborates [23] results, specifying that underground storage is the most profitable design for a flexible load electrolyser. [34] is the first to integrate a forecasting dimension while optimising the participation of the Power-to-Gas facility in the day-ahead market in Southern Sweden. Yet, the impact of using forecasted power prices, being imperfect predictions of future prices, has not been assessed. Furthermore, up to my knowledge, no study has built a clear analysis of how power price volatility and level affect profitability. Most of the papers, when it comes to performing a techno-economic analysis of water electrolysis and assessing its potential profitability, use the Levelized Cost of Hydrogen (LCOH) as a metric to assess the profitability. The latter is defined as the break-even hydrogen value [€/kgH_2] to cover the lifetime costs [37].

4 Bidding zone selection and price scenarios development

The overall objectives of this section are threefold. Initially, I present eight European bidding zones. I analyse the data on a seven-year time horizon through complementary statistical metrics. Based on this analysis, I select three market areas. These markets present significant differences in their data while remaining potentially interesting for the development of large-scale water electrolysis. Finally, for the next part of this master's thesis, I build price scenarios based on historical price observations. These scenarios will allow me to assess the profitability of Power-to-Gas under different market conditions.

In this section, I perform a day-ahead power price analysis to select only the most appealing market areas presenting significantly different price profiles. I make the preliminary analysis on the following bidding zones between the 5th of January 2015 and the 31st of December 2021: Spain (ES), Northern Italy (IT North), France (FR), Belgium (BE), the Netherlands (NL), Germany (DE), Western Denmark (DK1) and Southern Norway (NO2). These zones fit well the European power landscape. I choose Northern Italy among the different Italian zones for its volume traded and its interconnection with the European continent. Then, Western Denmark accounts for the highest share of both the Variable Renewable Energy Sources and the total power generation in Denmark. Finally, in Norway, I focus on the Southern market area as it combines both an important hydro-power generation and a good interconnection with the Netherlands and Western Denmark. It will also be soon interconnected with Great Britain through the North Sea Link cable project.

4.1 Day-ahead power prices analysis

I use different metrics to investigate the day-ahead power price differences. The analysis is split into three parts: descriptive statistics, correlation, and variability analysis.

4.1.1 Descriptive statistics analysis

This section follows [30]'s methodology to compare day-ahead power prices on a statistical dimension.

4.1.1.1 Mean price

Figure 3 displays the evolution of the average day-ahead prices in the studied countries. Several observations can be made from it.

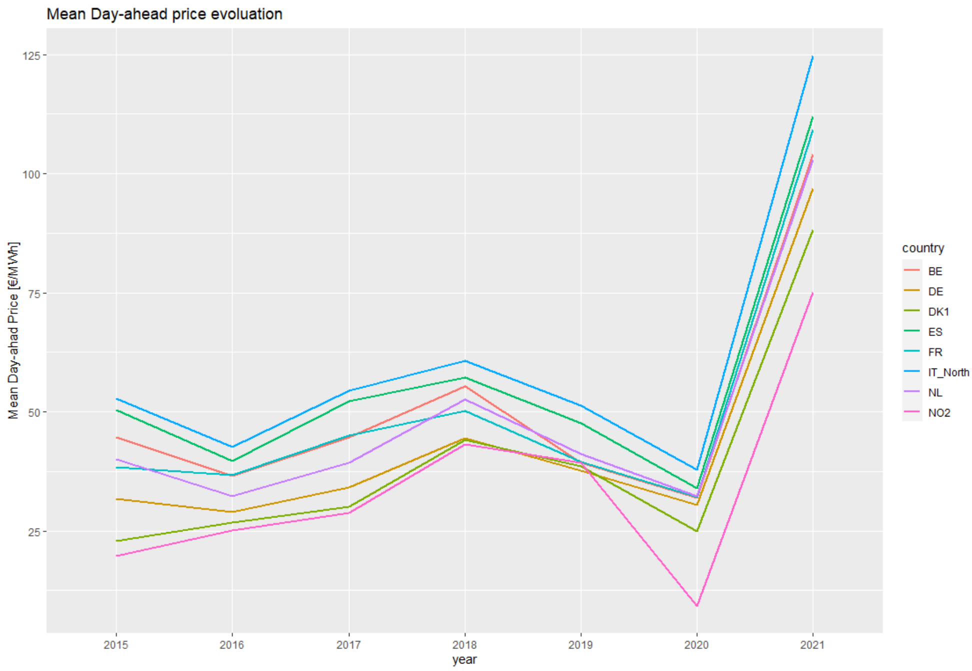

Figure 3: Mean day-ahead price evolution

Firstly, I can draw four price groups sharing common features regarding trend and average price. Southern market zones, Northern Italy and Spain, exhibit the highest prices of the sample. Then, Belgium, France, and the Netherlands show a similar mean price although their relative positions change over time. Next, Germany and Western Denmark get closer to the lowest price area, especially in 2018 and 2019 when the values are comparable. Finally, Southern Norway stands out in 2020 and 2021 as the cheapest market on average.
Overall, it is difficult to tie a common trend for the two first mean price groups. Their prices remain stable between 2015 and 2019. For the last two groups, the prices instead increase during the same period.

Secondly, all markets face a drop in electricity prices in 2020. The reasons are to be found in a lower demand, induced by the COVID-19 pandemic, and exceptional weather conditions all over Europe boosting the renewable production [32; 51].

Thirdly, prices skyrocket in Europe in 2021. Multiple and related causes can explain this electricity crisis. Natural gas demand raised in Europe, Variable Renewable Energy Sources were less available due to bad weather, mostly an unusual lack of wind and precipitations, and Europe was recovering faster than expected from the COVID-19 recession. Simultaneously Russia, the main gas importer, decided to cut down supplies for political reasons; the competition increased with Asia on the Liquefied Natural Gas market, and the main European gas suppliers, the Netherlands and Norway, also faced production problems. These tight market conditions combined with higher carbon prices have led to this situation [7; 64].

4.1.1.2 Dispersion

To study day-ahead prices dispersion between 2015 and 2021, I draw box plots in *Figure 4*. In this figure, I limit the y-axis scale from -50€/MWh to 75€/MWh to better show price dispersion.

The time-evolving dimension of the graphs allows to highlight the evolution of the price profiles in the studied areas. Overall, a convergence between the market areas can be observed. While, the four groups pointed out in the previous section still stand out between 2015 and 2018, groups start to congregate from 2019. In 2019, the dispersion and price levels of Germany and Western Denmark are comparable to the Belgian, French, and Dutch. In 2020, Spain and Northern Italy come along. Finally, in 2021, Southern Norway also undergoes higher prices like the other market areas.

The Norwegian and Southern European bidding zone groups are confirmed regarding the price dispersion. They respectively display lower and higher prices than any other area. In addition, the Norwegian market area has also a smaller box size, implying that most of the prices are located around the median.

On the opposite way, Western Denmark and Germany can be differentiated even if their price levels are still comparable. From 2015 to 2019, Western Denmark has a smaller dispersion and lower price levels. In 2020 and 2021, Western Denmark has a higher dispersion but lower first quantile and third quantile. In 2020, the first quantile of Western Denmark is even located in the negative prices.

In Section 4.1.1.1 Belgian, French, and Dutch mean day-ahead price behaviours were difficult to apprehend. Regarding their price dispersion, Belgium goes along with France whereas the Netherlands shows slightly smaller dispersion and price levels over the years.

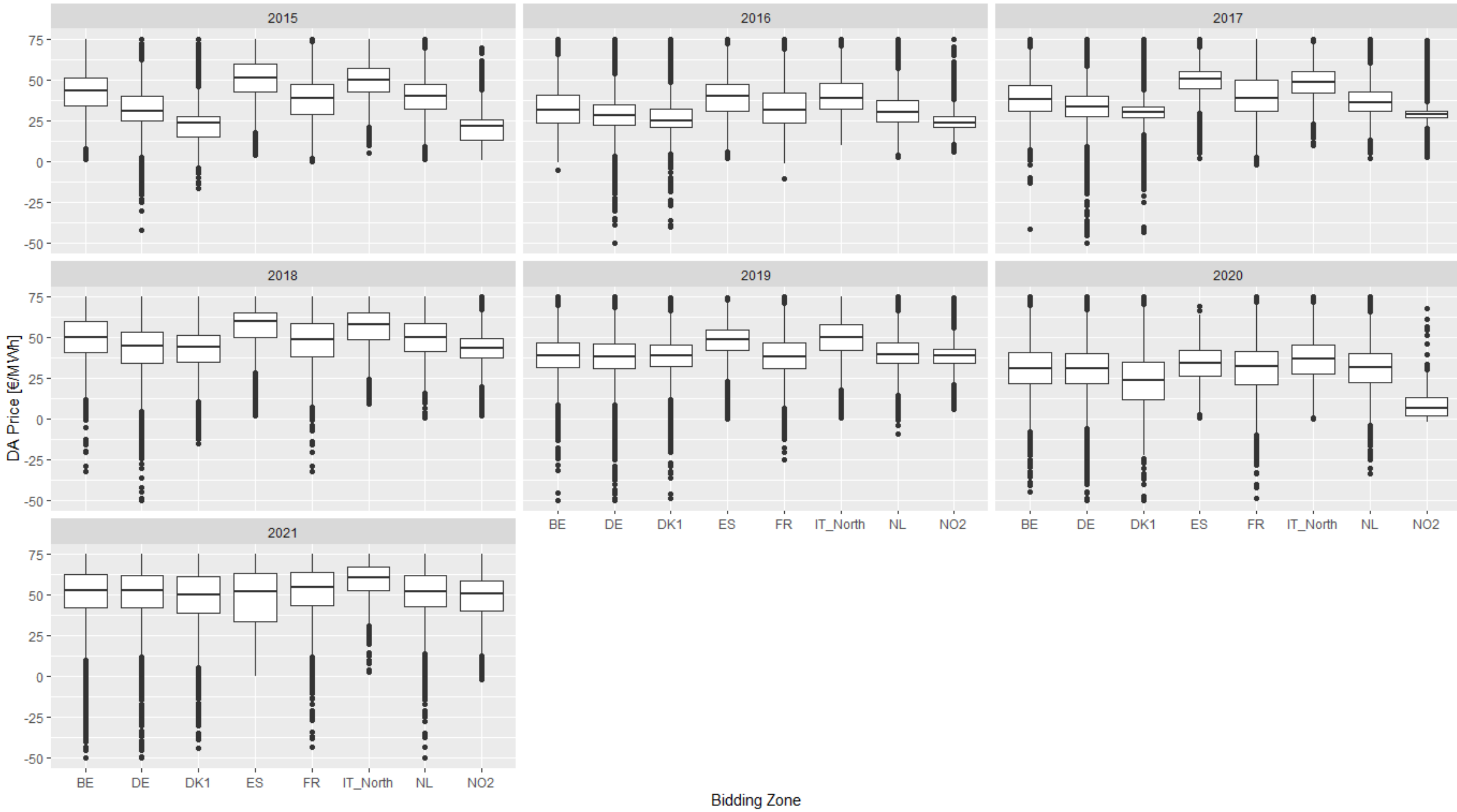

Figure 4: Ordinate limited day-ahead prices boxplots

4.1.1.3 Outliers

In the power market, extreme situations, both positive and negative, are interesting to investigate. For a flexible Power-to-Gas facility, lower price periods should be exploited to consume power and thus produce hydrogen at a cheaper cost. The full-range day-ahead prices box plots can be found in Appendix A.

Belgium and Germany stand out with respectively positive and negative outliers between 2015 and 2018. Western Denmark goes along with Germany in 2016 and 2017 to a lower extent. The negative power prices are profitable to Power-to-Gas businesses. They are caused by base-load coal and nuclear power plants being ready to pay negative prices to avoid shutdown costs when the generation is dominated by cheap renewable means. The number of negative price periods confirms this situation observed in the bidding zones over the seven-year time horizon studied (*Table 1*).

DE	**NL**	**IT_North**	**NO2**	**DK1**	**ES**	**BE**	**FR**
1135	170	0	10	661	0	383	210

Table 1: Number of negative price hours between 2015 and 2021

Exceptional market conditions are visible in the outliers distributions both in 2020 and 2021. In 2020, Germany, Belgium, Western Denmark, France, and the Netherlands display an important number of negative prices while all market areas show positive an unusual number of positive outliers in 2021.

The maximum price ever recorded in the data set is reached in France on the 7th November 2016 at 874.01€/MWh. In 2021, on 21 December, the maximum price of 620€/MWh is achieved simultaneously in Germany, Denmark, Belgium, the Netherlands, and France. The lowest price is observed on the night of the 6th of August 2019 in Belgium, with a level of -500€/MWh.

4.1.2 Correlation analysis

Since 2014, the European Commission is determined to increase the interconnection capacity in the power system. The potential benefits of interconnectors are indeed numerous: higher integration of European power markets, better investment signals for power generation capacity, higher integration of Variable Renewable Energy Sources, increased security of supply, and support to the industrial low-carbon industries [18]. Interconnection between European bidding zones influences the price level. This section has therefore as objective to study the overall correlation between the day-ahead prices.

Figure 5 presents the correlogram of day-ahead prices between 2015 and 2021. The Pearson's coefficient, r, is used to evaluate the linear relationship between the bidding zones. In Appendix B, the correlation matrix is presented, highlighting the price distributions in every area, the correlation coefficient r, and its significance. Without surprise given the current interconnection level, most of the markets are either very highly correlated (r between 0.9 and 1) or highly correlated (r between 0.7 and 0.9). More precisely:

- **DE**: is very highly correlated with NL (0.930), DK1 (0.930), and FR (0.903).
- **NL**: is very highly correlated with FR (0.935), DE (0.930), BE (0.928), and IT_North(0.925).
- **IT_North**: is very highly correlated with FR (0.937), ES (0.929) and NL (0.925).
- **NO2**: does not have a very high correlation with any country. It is however highly correlated to all other market zones.
- **DK1**: is very highly correlated with DE (0.930).
- **ES**: is very highly correlated with IT_North (0.929) and FR (0.903).
- **FR**: is very highly correlated with BE (0.951), IT_North (0.937), NL (0.935) DE (0.903) and ES (0.903).
- **BE**: is very highly correlated with FR (0.951) and NL (0.928).

Neighbouring countries, therefore, influence their respective price levels. Based on the correlation, the group classification highlighted in Section 4.1.1.1 still stands.

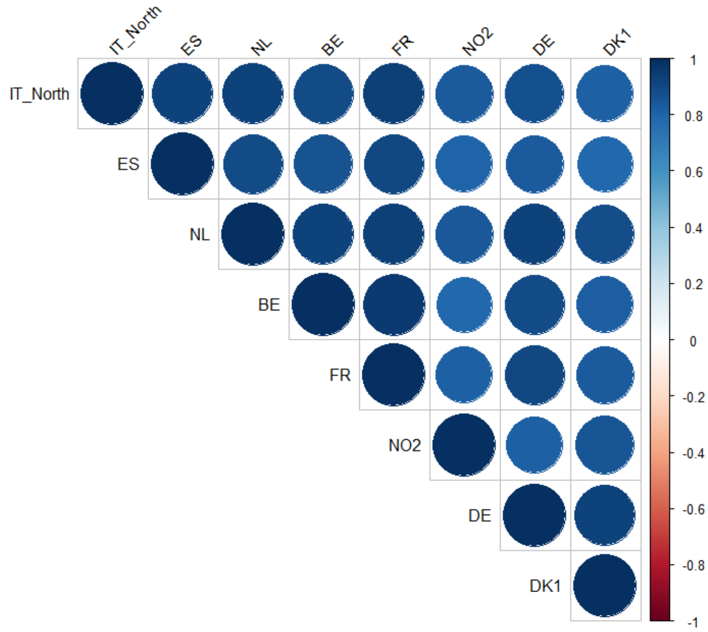

Figure 5: Day-ahead prices correlogram

4.1.3 Variability analysis

To better apprehend how power prices behave within a given time horizon, I investigate the variability. Several metrics exist to assess the power price variability. Instead of choosing the standard deviation as a variability estimator, I choose the maximum price difference for the water electrolysis context [61]. This measure reflects extreme power price values. It is then suited to arbitrage problems. I only take one observation for maximum and minimum values to exacerbate the differences between bidding zones. The maximum price difference Δ is defined over a time horizon t as:

$$\Delta_t = \max x_t - \min x_t \tag{3}$$

where x_t are the day-ahead prices over period t.

For this analysis, following [61]'s example, daily, weekly, and monthly variability are investigated. *Figure 6* presents the mean and the standard deviation of the variability observed over the seven years data set[2]. Detailed evolution of the variability over the years is presented in Appendix C.

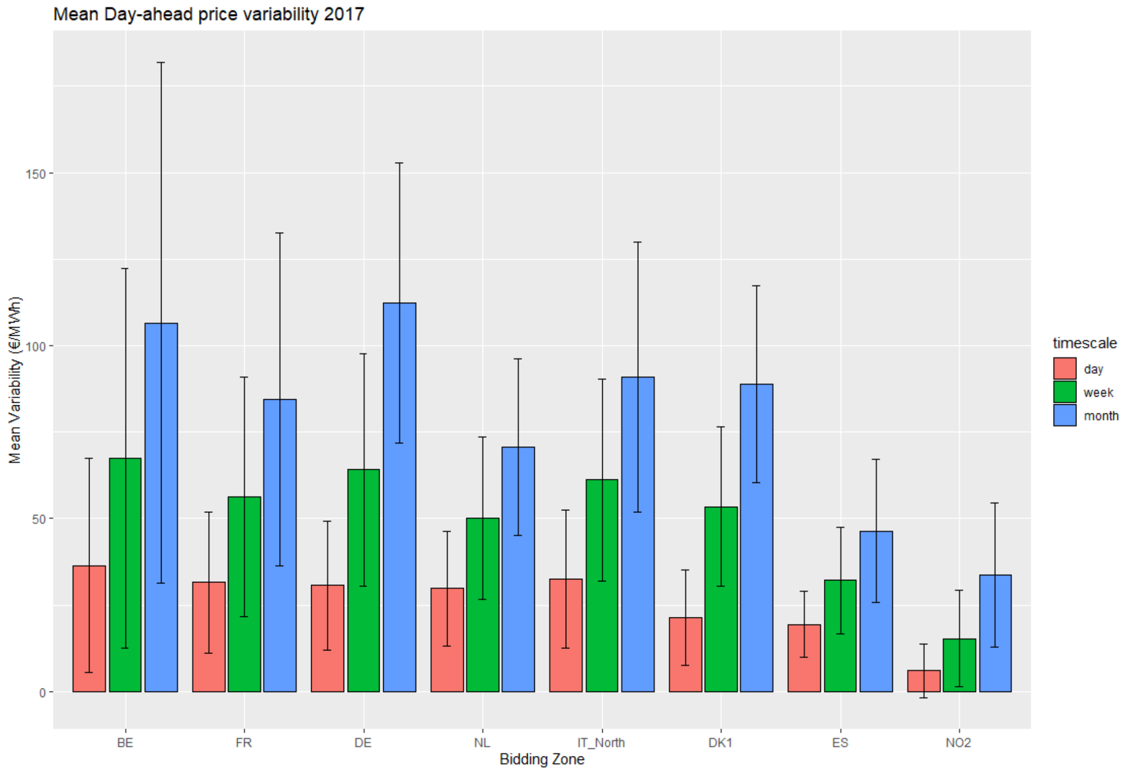

Figure 6: Daily, weekly and monthly mean variability

I perfrom Student and Fisher tests to respectively check if the mean variability and the standard deviation of the distributions were equivalent. Summary diagrams can be found in Appendix D.

Overall, the longer the timescale is the more the areas share common variability features. Daily, Germany and the Netherlands are behaving equivalently. Weekly, the Netherlands and Western Denmark do. Finally, monthly, there are four equivalency relationships: Belgium-France and the Netherlands - Germany - Denmark. Globally, in terms of variability, Belgium stands out from France and the Netherlands. Furthermore, Western Denmark and Germany only share common variability monthly. No relationship is observed between Norway and Denmark,

[2]With the representation of the standard deviation, negative values are obtained. This can be explained as the bars represent the mean of the maximum differences observed and the error lines the standard deviation of the latter. Such representation as in the figure assumes a Normal distribution. In practice, a Normal distribution is not present but it has been decided to keep it that way to show the variation in the mean of the maximum differences.

between Belgium and the Netherlands, and between Italy and Spain. Belgium displays the highest variability of the data set. The Norwegian area has the lowest price variability.

4.2 Bidding zones selection

I can now summarise findings to select the bidding zones further studied. I mostly base the decision on the day-ahead prices and the price variability. These metrics are indeed influencing the most water electrolysis businesses. I use the other parameters studied to differ countries sharing the same features. *Figure 7* highlights the relationship between yearly mean day-ahead prices and daily day-ahead price variability[3]. I choose daily timescale to represent the variability dimension as, as shown in Appendix D, few equivalency relationships are demonstrated with this time horizon.

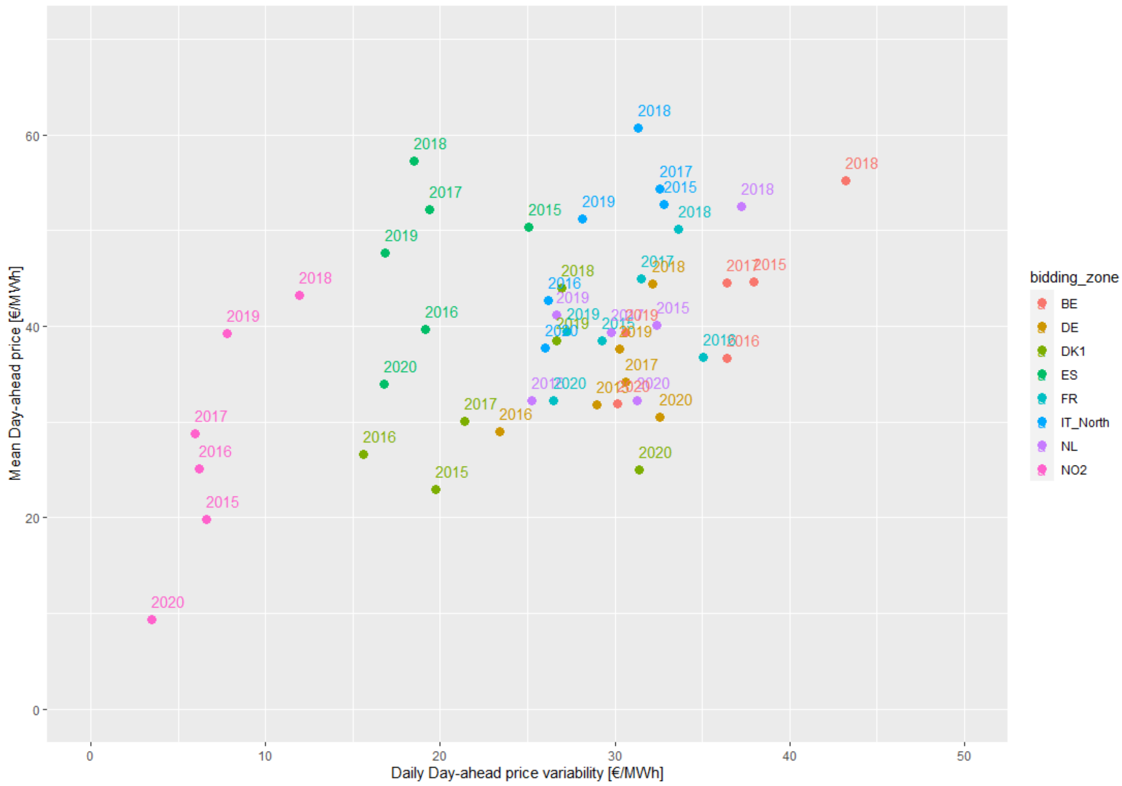

Figure 7: Mean day-ahead price and daily day-ahead price volatility

[3]In this graph, the year 2021, presenting higher prices and variability, has not been plotted to better visualize data.

To begin, I identify Northern Italy and Spain as the most expensive areas in the study set. These zones are also very highly correlated according to Pearson's coefficient. Spain presents a lower variability than Italy on every time horizon. Spain has electricity prices and low variability. It thus does not appear to be suitable for the development of electrolysis. Even though Northern Italy has a higher variability, compared to other studied areas, it does not seem sufficient neither to overcome its high prices. These two areas will thus not be more investigated.

Next, Germany and Western Denmark could be seen as equivalent in terms of mean price even if Germany shows a slightly higher mean price over the years. However, the dispersion analysis displays different price profiles. Western Denmark offers lower price levels. The correlation analysis demonstrates that prices in both zones are also very highly linearly correlated. Except monthly, the variability between the two bidding zones is different, with Germany having a higher daily and weekly variability. Their variability remains however on the same scale when compared to other areas.
For this master's thesis, I decide to keep the Western Danish area and to drop Germany. As highlighted in Section 3.1, Germany is leading by far among European countries in the development of Power-to-Gas. This gives already good incentives to the market. Moreover, Western Denmark exhibits more differences, in terms of correlation and variability, with other market areas than Germany.

Then, Belgium, the Netherlands, and France share several common features. They display equivalent high mean prices and are very highly correlated. Nevertheless, Belgium emerges with higher variability while France and the Netherlands are closer to Germany and Western Denmark in terms of correlation and variability. Belgium, daily and weekly, is independent. With the integration of Variable Renewable Energy Sources, power price variability will increase [42], it is then interesting to study how Power-to-Gas can perform in this context. Belgium is thus selected for the next parts. France and the Netherlands are dropped as they share common features with Western Denmark.

Lastly, Southern Norway has the lowest price profile. Its variability is also low. Furthermore, Southern Norway is more independent than any other studied market area. For all these reasons, Southern Norway will be further investigated.

Overall, I consider three price areas: **Belgium** (high prices, high variability), **Western Denmark** (average prices, average variability), and **Southern Norway** (low prices, low variability). This selection can be easily differentiated from other areas in *Figure 7* comforting the choice. The differences between these bidding zones also extend to the generation mixes as shown in Appendix E. In 2021, Belgium still relies at 51% on nuclear power plants, followed by gas (21,6%). Wind and solar generation account for 18,2% in 2021. Denmark, on the opposite, mostly rely on wind power (48,6%) and other renewable sources, i.e. biomass, and waste, geothermal, wave and tidal (21,3%). Fossil fuels (coal, gas, and oil) generate 26% of the electricity in 2021. Norway bases its production on hydro-power (91,7%) and to a lesser extent on the wind (7,4%) [58].

4.3 Scenarios development

Future power market conditions are rather unpredictable and depend on numerous reasons: generation mixes, weather conditions, carbon prices, policies, or other political events. Instead of trying to forecast how the market will behave in next decades, the vision of this master's thesis is to build price scenarios based on historical data to assess the profitability of investments in water electrolysis. If market conditions comparable to the one used in the price scenarios are observed, the investor will be able to assess the profitability of a water electrolysis facility. *Figure 8* focuses on the three selected bidding zones.

At first sight, 2021 sticks out. For every bidding zones, it represents the highest combination of mean price/daily volatility. These market conditions could take place in particularly uncertain and unfavorable environments for water electrolysis. Even though these conditions are less favorable, they might still happen in the future making an assessment necessary.

Moreover, 2020 demonstrates interesting features. For Southern Norway and Belgium, the lowest combination of mean price / daily volatility. In Western Denmark however, while the average price is low, the market achieves its highest volatility fostered by a high share of Variable Renewable Energy Sources in these bidding zones.

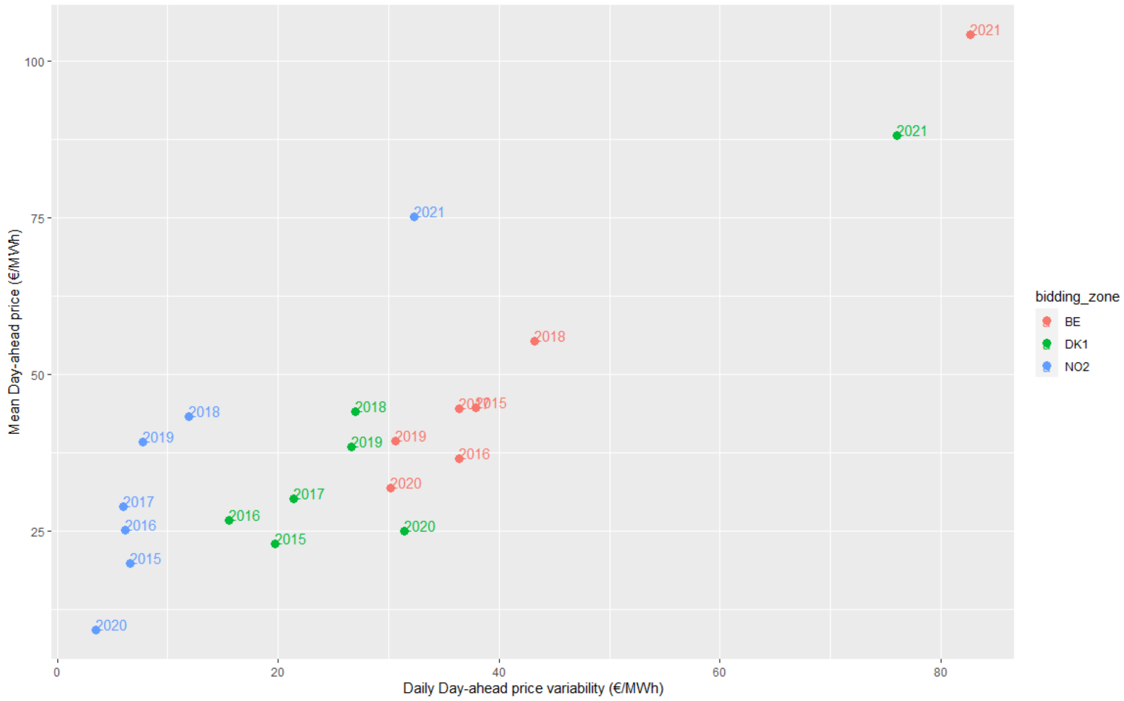

Figure 8: Mean day-ahead price and daily day-ahead price volatility

On its side, 2017 could be seen as an intermediate scenario for every bidding zone with average mean price and average volatility compared to the studied years. Scenarios are summarised and presented in *Table 2*.

Parameter	**Scenario 1**	**Scenario 2a**	**Scenario 2b**	**Scenario 3**
Historical data year	2021	2020	2020	2017
Bidding zone covered	BE-DK1-NO2	BE-NO2	DK1	BE-DK1-NO2
Features	High Prices and High Volatility	Low Prices and Low Volatility	Low Prices and High Volatility	Intermediate Prices and Volatilty
Scenario name	**2021 HPHV**	**2020 LPLV**	**2020 LPHV**	**2017 IPV**

Table 2: Price scenario summary

5 Day-ahead power price forecasting

This section has a final target to produce twenty-four hours ahead power price forecasts for the selected price areas under the different scenarios. This output will be used in an optimisation algorithm to simulate the behaviour of water electrolysis sourcing its electricity consumption in the day-ahead market. As a first step, I briefly describe the current knowledge in electricity price forecasting. Then, I apply a four-step methodology to select the appropriate forecasting model and predict the day-ahead prices.

Power-to-Gas facilities rely on price forecasts to schedule and optimise properly their power consumption profiles. The Crystal Ball scenario, i.e. a perfect knowledge of future electricity prices, is unrealistic. Electricity price forecasts have to be used to model the price uncertainty undergone by energy businesses.

[41] summarises and describes different forecasting techniques. The author highlights two methods that are mostly covered by the literature for short-term electricity price forecasting: artificial intelligence and statistical modeling.
Artificial Intelligence is constituted of artificial neural networks. The latter is most likely to outperform other techniques [40] thanks to their ability to deal with complex data and potential price spikes [41]. However, this complexity also leads to higher computational time [40]. Statistical methods, including time series analysis, due to their relative simplicity, have seen the number of publications in the literature increase since 2016 [41].

Statistical techniques are composed of different methods: exponential smoothing, regression models, AR/AR-X type, threshold AR, and GARCH-type. Auto-Regressive Integrated Moving Average (ARIMA) models are considered "one of the most recognised and used models" in electricity price forecasting. ([35], p.5). The master's thesis intends to give a benchmark of the profitability when optimising day-ahead nominations. I thus further use ARIMA models. A Detailed description of ARIMA models can be found in [29; 35].

One important advantage of ARIMA models is their ability to describe complex seasonality, such as observed in power markets (daily, weekly, and yearly). It can be modeled through the addition of Fourier terms, combining a harmonic regression with the ARIMA model [29]. As a general rule, the model minimising the AICc criteria is selected as the best fit [29].

[8] has developed a four-step methodology to fit ARIMA models and to use them to forecast electricity day-ahead price. Comparable methodologies can be found in other papers and reference books [29; 35].

5.1 Step 1: Model identification

Times series data have first to be completely visualized. It helps to determine the ARIMA model that should be used. Time series must verify the stationarity assumption. Next, an auto-correlation analysis is performed.

5.1.1 Stationarity

Day-ahead prices are plotted in Belgium in *Figure 9*. As observed and analysed in the Section 4.1, prices display an unusual behaviour with an increased proportion of negative prices in 2020 and an increasing price trend in 2021. However, overall, the data seems rather stationary. Comparable behaviours can also be found both in Southern Norway and Western Denmark (Appendix F).

I perform Augmented Dickey-Fuller Tests for every bidding zones and the whole data set to verify the stationarity. Belgium, Western Norway, and Southern Denmark reject the non-stationary null hypothesis with a p-value lower than 0.01 (Appendix G).
The time scale used in *Figure 9* prevents observing the seasonality of data. *Figure 10* zooms on a month window (April 2017) in Belgium. A daily and weekly seasonality can be observed. The latter is verified in the next steps.

5.1.2 Auto-correlation analysis

To confirm the seasonality observed in Section 5.1.1, an auto-correlation analysis is performed.

I plot Auto-correlations from the three bidding zones on the same graph for a better comparison. The significance threshold is not plotted as all observations are above. *Figure 11*

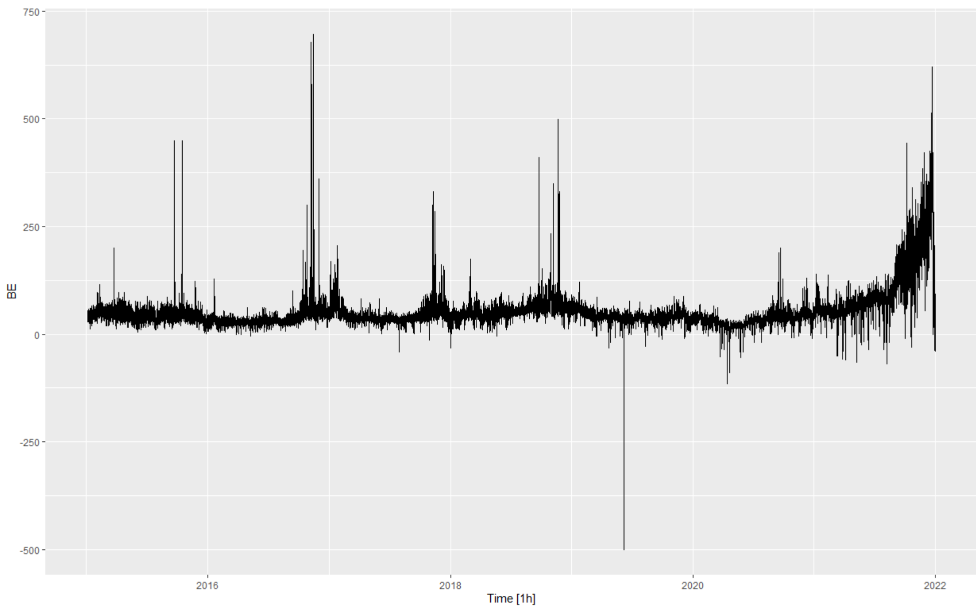

Figure 9: Belgian day-ahead power prices [€/MWh]

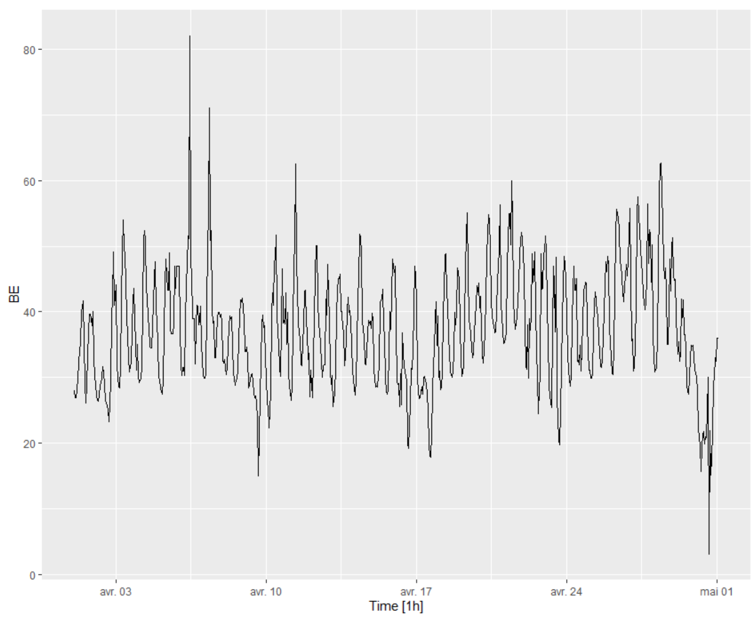

Figure 10: Belgian day-ahead power prices in April 2017 [€/MWh]

displays the ACF until lag 168. For Southern Norway (NO2), maximums are observed every 24 lags and at lag 168 suggesting daily and weekly seasonality. Belgium and Western Denmark also display maximums every 12 lags hinting half-day seasonality. [4; 35] also suggest the presence of a half-year (winter-summer / autumn-spring) and yearly seasonality in hourly power data. Nevertheless, because only twenty-four hours are forecasts are needed, I will not investigate these dimensions to keep the model simple. I build Partial Auto-correlations in

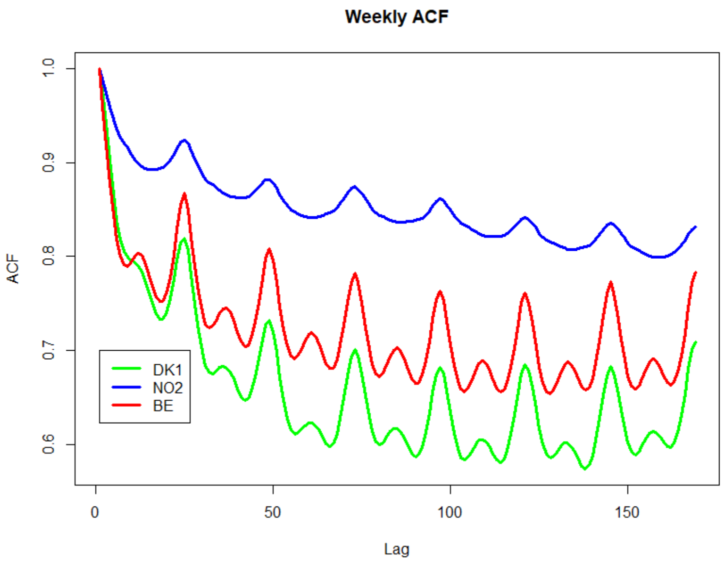

Figure 11: Weekly ACF

Appendix H to confront these results with the ACF graphs. Daily and weekly seasonality are confirmed there for the three bidding zones. However, the twelve-hour seasonality is rejected for Belgium and Western Denmark as the pACF value is within the significance threshold. Surprisingly, the 12th lag in the pACF is significant for Southern Norway. However, to keep the models comparable between the bidding zones, I decide to not model it.

5.2 Step 2: Parameters estimation

Section 5.1.2 highlights two seasonal dimensions: day and week. [29] recommends the introduction of Fourier terms to model complex seasonality. Fourier series, for periods 24 (day) and 168 (week), are modeled as followed:

$$\sin\left(\frac{2\pi kt}{24}\right), \cos\left(\frac{2\pi kt}{24}\right), \sin\left(\frac{2\pi kt}{168}\right), \cos\left(\frac{2\pi kt}{168}\right) \tag{4}$$

Where k is the order of the series. The latter should be chosen for each seasonality to minimise the AICc.

In this master's thesis, I simulate an important number of days. Simultaneously, my computation resources used to write the master's thesis are limited. An appropriate balance between fitting accuracy and computation time has to be found. Therefore, a training set of 1 month is used to estimate ARIMA's parameters. This window allows capturing both daily and weekly seasonality with a sufficient number of observations while keeping the training set relatively small. Moreover, the higher the order is and the more complex becomes the model. Orders have thus been fixed subjectively such as K is equal to 2 and 1 respectively for daily and weekly seasonality. I implement the following code for every bidding zones:

```
fit <- training_set %>% model(
  fmod = ARIMA(BiddingZone ~ PDQ(0, 0, 0) +
                         fourier(period = "day", K = 2) +
                         fourier(period = "week", K = 1)))
```

I set PDQ() at (0,0,0) so Fourier terms handle the seasonality. I don't specify the pdq() dimension so ARIMA() chooses the components minimising the AICc. The latter is therefore not fixed and changes with the training set.

5.3 Step 3: Model's hypotheses verification

Now that I have fitted a model, I check the residuals to confirm if they are consistent with white noise. However, as shown in *Figure 12*, for Belgium, residuals do not display such behaviour with several significant lags and non-normal distribution. Southern Norway and Western Denmark have also comparable residuals features (Appendix I). The model could therefore be adapted by modifying Fourier's orders. However, such manipulations drastically increase the computation time. By heuristic, after several tries, no significant changes were observed when increasing Fourier's orders highlighting the complexity of hourly power market data. The initial orders are thus kept. Even if the residuals' behaviour should be seen as a drawback, it is important to remind that it is complicated to capture all the interactions with such complex data.

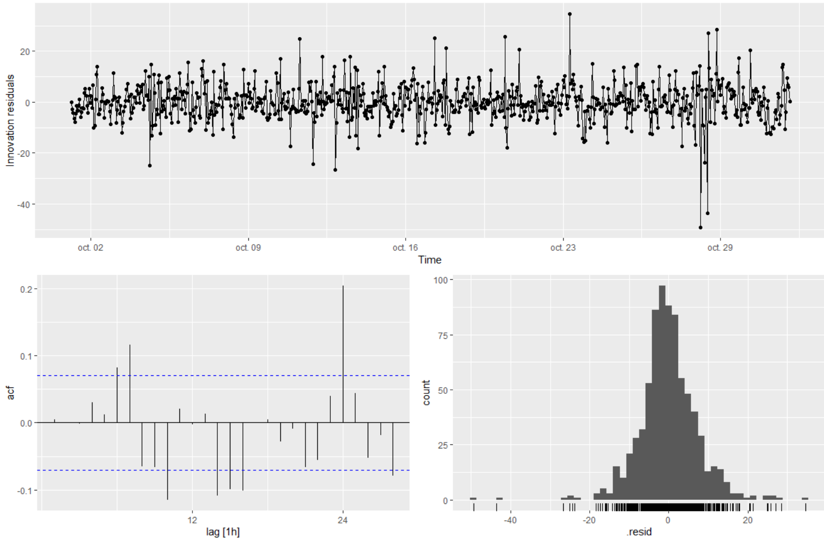

Figure 12: BE residuals

5.4 Step 4: Forecasts

I can now forecast day-ahead power prices. *Figure 13* shows the output obtained with both points and intervals forecasts. It also shows that my model successfully manages to replicate the seasonal patterns.

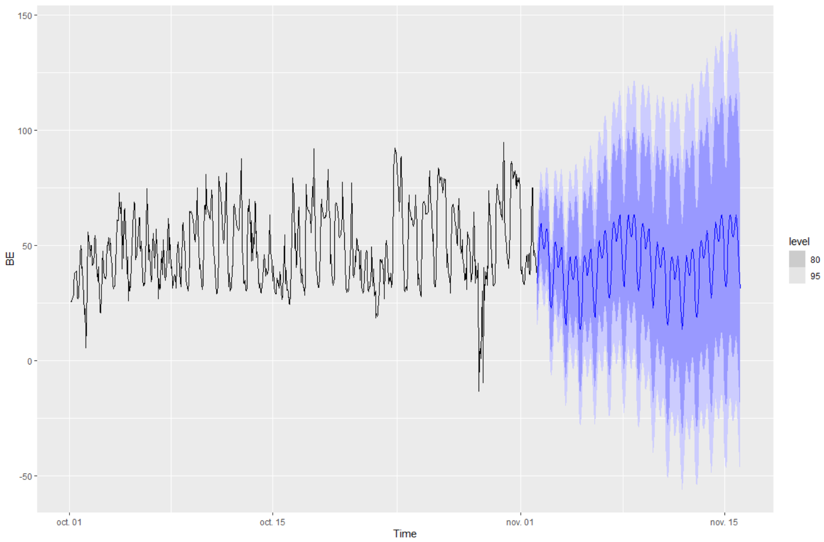

Figure 13: Day-ahead Price forecasts in Belgium [€/MWh]

5.5 Forecasts performance

I automatise the procedure to simulate the day-ahead forecasting in the four price scenarios highlighted in Section 4.3. Practically, it means that the model is taking the last month of data as a training set to forecast the next twenty-four hours of prices. The model is then actualised every day by including new observations. This process is illustrated in *Figure 14*.

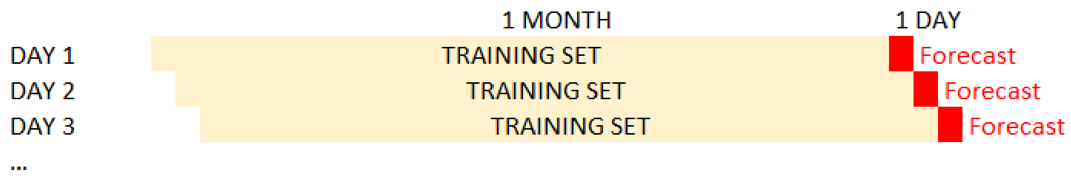

Figure 14: Simulation process

An example of the forecasting results is displayed in *Figure 15*. The model manages to capture the overall trend and behaviour of the day-ahead prices. However, even if the timing is correct, the model fails to fit the spikes observed.

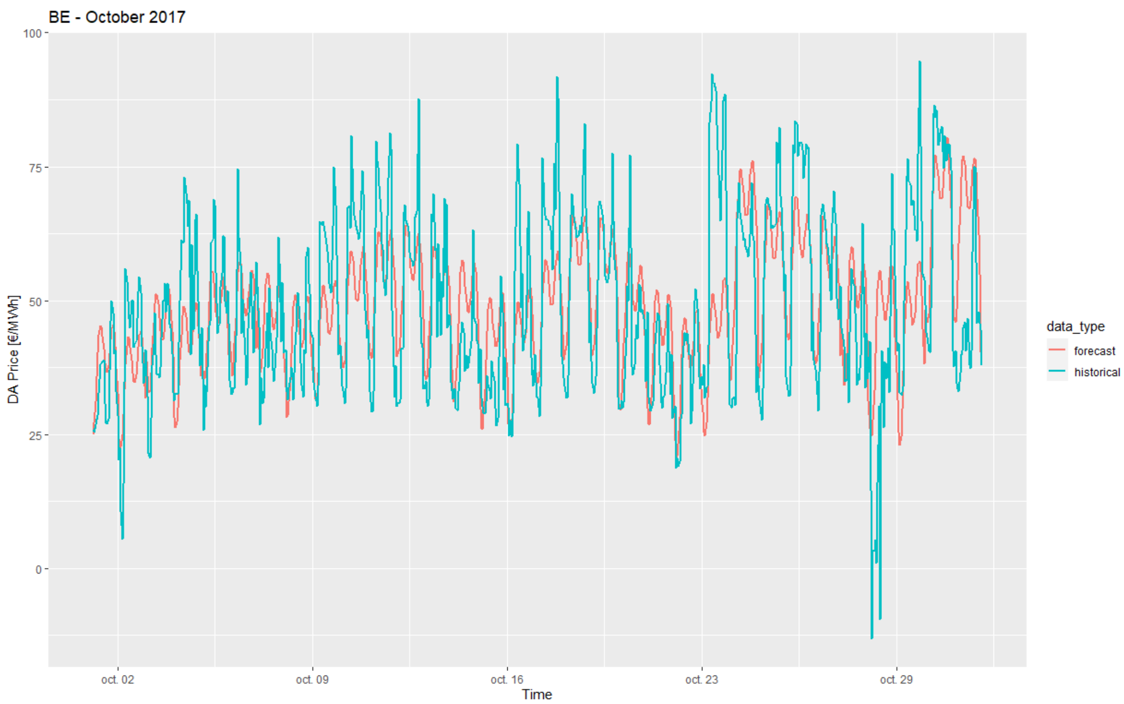

Figure 15: Forecasting results - Belgium October 2017

The overall performance of the forecasts can be measured by the Mean Absolute Error (MAE).

The MAE is defined by the following formula:

$$MAE = \frac{\sum_{i=1}^{n} |x_i - y_i|}{n} \tag{5}$$

where n is the number of observations, x the observed price, and y the forecasted price.
In general, in forecasting theory, the Mean Absolute Percentage Error (MAPE) is preferred, but in our case, where prices can have a zero value, this metric is not usable. Simulations MAE can be found in *Table 3*.

Scenario / Bidding Zone	2017 IPV	2020 LPLV	2020 LPHV	2021 HPHV
BE	8.18	6.62	Non Applic.	19.85
DK1	6.13	Non Applic.	9.16	21.25
NO2	1.67	1.15	Non Applic.	10.52

Table 3: MAE under different price scenarios

Under the different scenarios, Belgium's MAE follows a straightforward behaviour. When the volatility and the prices are at their lowest level (2020), the MAE is at its lowest level and is increasing when these two parameters are increasing. In Western Denmark, the high volatility period (2020) induces a lower performance of the forecasting method. When disturbances are present in the market in 2021, the forecast displays the worst performance in this bidding zone. In Southern Norway, the forecasts are performing well in 2017 and 2020 when the volatility and the prices were low. The forecast's performance is worsened by almost a ten factor when the prices and the volatility increase such as in 2021. Plots of forecasts versus actual prices can be found in Appendix J.

6 Case study

The aims of this section are threefold. As a first step, I describe the overall structure of the case study. In a second time, I define every parameter influencing the computation of the Levelized Cost of Hydrogen. I also review the current scientific knowledge to estimate every technical and cost component.

In this section, I model a water-electrolysis facility in the three selected bidding.
Recall, the most profitable business model for water electrolysis is to act as an end-use flexibility tool, providing "Electricity-based Hydrogen" to the market. *Figure 16* describes the different flows of the case study modeled. The electrolyser, either based on Alkaline or Polymer Electrolyte Membranes Electrolysis, is directly connected to the grid as any other industrial consumer. Once the hydrogen is produced by the electrolysis, it is compressed, placed into a storage facility, or directly supplied to the market. The detailed features of every component are described later in this section. I consider that both the oxygen and heat produced during the process are not valorised and released into the atmosphere.

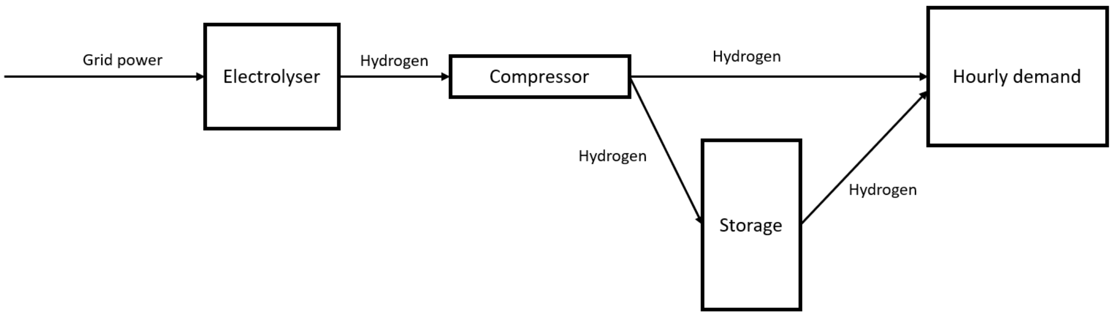

Figure 16: Case study facility

The Levelized Cost of Hydrogen (LCOH) is used to investigate the profitability of a Power-to-Gas facility. The Levelized Cost of Hydrogen is defined as the Net Present Value of the lifetime production costs divided by the Net Present Value of the lifetime of the hydrogen produced. Similarly, it could be defined as the break-even hydrogen value [€/kgH_2] to cover lifetime costs [37]. Mathematically, it can be also translated by equation 2 [26; 48; 50].

This metric includes both critical dimensions highlighted by [34; 50; 66], being the power price levels and the number of operating hours necessary to cover investments.
Just like [62], a description of each component of the Levelized Cost of Hydrogen is made in the next parts of this section. A review of the literature is also performed to use appropriate parameters' values in the next steps.

6.1 Electrolyser & compressor

Several technologies of water electrolysis currently exist but only two are commercially available: Alkaline Electrolysis and Polymer Electrolyte Membranes Electrolysis. Alkaline Electrolysis is the most mature and has been considered the most cost-efficient technology on the market. Its main competitive advantage was a lower CAPEX, accounting for more than 30% of the overall costs [50], and a longer cell stack life expectancy. As the most mature technology, the cost estimation in the literature is also very convergent [50]. On the other hand, Polymer Electrolyte Membranes Electrolysis enjoys much more flexibility with a faster reaction time. Soon, Polymer Electrolyte Membranes Electrolysis is expected to outperform Alkaline Electrolysis due to a significant decrease in the CAPEX [34] and a higher scale-up effect. However, the uncertainty is still important regarding the timing and the potential improvements. Many studies offer different estimations and forecasts of cost reductions.

6.1.1 Electrolyser CAPEX

In the literature, different study cases are assessed with different assumptions. Nevertheless, economies of scale are possible with water electrolysis [23]. To compare the different CAPEX values, [13] methodology is used:

$$CAPEX_x = \frac{CAPEX_{base} * K_{base} * (\frac{K_x}{K_{base}})^{\alpha}}{K_x} \tag{6}$$

where $CAPEX_{\mathrm{x}}$ represents the new CAPEX value [€/kW], $CAPEX_{\mathrm{base}}$ is the initial CAPEX value [€/kW], K_{x} the new capacity [kW], K_{base} the old capacity [kW] and α the scaling component. The value of α is usually set to 0.6-0.7 by reference to the so-called "six-tenths or seven-tenths rule" [13]. For mature technology, such as Alkaline Electrolysis, α is set to 0.85 by [37; 62].

Technology	Studied capacity [kW]	Publication year	Studied year	CAPEX [€/kW]	α	CAPEX Capacity Adapted (100MW) [€/kW]	Source
AEL	6,000	2018	2018	800 - 1,500	0.85	525-984	[6]
AEL	2,000	2019	2019	750	0.85	417	[54]
AEL	100,000	2019	2030	400	0.85	400	[54]
AEL	1,074	2020	2020	830	0.85	420	[34]
AEL	1,074	2020	2030	730	0.85	370	[34]
AEL	1,074	2020	2050	640	0.85	324	[34]
AEL	*582.19*	*2022*	*2022*	*750*	*0,85*	*347*	*[20]*
PEMEL	2,000	2018	2018	1,400-2,100	0.7	432-649	[6]
PEMEL	5,000	2019	2019	750	0.7	305	[54]
PEMEL	1,074	2020	2020	1,130	0.7	290	[34]
PEMEL	1,074	2020	2030	800	0.7	205	[34]
PEMEL	1,074	2020	2050	570	0.7	146	[34]
PEMEL	*662.1*	*2022*	*2022*	*1200*	*0.7*	*266*	*[20]*

Table 4: CAPEX and CAPEX adjusted [€/kW] for Alkaline (AEL) and Polymer Electrolyte Membranes (PEMEL) Electrolysis

Table 4 is built to compare the actual capacity-adapted estimations of the CAPEX for both technologies with the current value used in the literature. [50] specifies that the expected electrolysis project size for the next decade is between 10 and 100 MW. This analysis is consistent with the recent Refhyne II project presented in Section 3.1. Moreover, as scaling-up capacity improves the economical situation of water electrolysis [23], a 100MW capacity is further used and is in line with [50; 62] works. The scaling-up component α of Polymer Electrolyte Membranes Electrolysis is fixed to its highest value, 0.7, according to the "six-tenths or seven-tenths rule" [13].

As expected, the CAPEX estimations for the Alkaline Electrolysis are much more convergent than for the Polymer Electrolyte Membranes Electrolysis because it is a mature technology. From [54], I have a reference value of a 100 MW Alkaline Electrolysis. This value is in line with [34]. However, the last estimations computed in 2022 are much more optimistic [20]. [20] does not provide the actual capacity in kW of the electrolysis. It had to be computed manually from their data and assumptions. I must therefore be cautious about these results. [34] includes as well the CAPEX of the compressor.

Yet, regarding the Polymer Electrolyte Membranes Electrolysis, both [20; 54] are in line with [34] predictions. This technology enjoys a smaller α improving the scaling-up effect. The CAPEX of Polymer Electrolyte Membranes Electrolysis is already lower than the Alkaline technology as 100MW is not common yet for electrolysis, but will be shortly. It is however coherent with predictions made by [34] where Polymer Electrolyte Membranes Electrolysis is expected to outperform Alkaline Electrolysis. Uncertainty is however much higher and a sensitivity analysis will therefore be necessary.

For the case study, I derive both values from [34] estimations: 420 €/kW and 290 €/kW for respectively Alkaline and Polymer Electrolyte Membranes Electrolysis. These estimations also include the compressor's CAPEX.

Outside the main investment costs, [50] is going further by including indirect costs in the computation. Site preparation, engineering design, project contingency, licensing fee, and upfront permitting cost would add 24.1% of the CAPEX to the initial costs.

6.1.2 Electrolyser $\mathbf{OPEX_{var}}$

This component is dominated by the cost of power consumption. The latter is detailed in Section 7 and depends on the bidding strategy and the day-ahead optimisation. This dimension is the only geographical-dependent component of the Levelized Cost of Hydrogen. This is through the latter that I assess the impact of market conditions on the Levelized Cost of Hydrogen.
Water is also part of the variable cost structure. However, its impact on profitability is considered as low. Water costs are negligible and should only be considered when there are issues with the supply [62; 68]. This dimension will therefore not be investigated in the master's thesis.

6.1.3 Electrolyser $\mathbf{OPEX_{fix}}$

Beside the variable part, $OPEX_{\text{fixed}}$ are included in the OPEX and are referred to as a percentage of the CAPEX. They cover all the range of operations to operate and maintain the electrolyser: cleaning, maintenance, etc. [62] summarises that they are estimated between 2 and 5% of the CAPEX for Alkaline technology but often reduced to 2-3%. [20] estimates them, both for Alkaline and Polymer Electrolyte Membranes Electrolysis at 2% of the CAPEX while [34] estimate them to 4%. However, these studies might underestimate the $OPEX_{\text{fixed}}$ component. [50] represents the most complete techno-economic analysis found in the literature and estimate them to 13.1%. This important difference from the rest of the scientific knowledge is justified by the inclusion of labor costs, compressor maintenance, insurance, property taxes, and different permits. This value is applicable for both water electrolysis technologies.

6.1.4 Lifespan of the facility and cell stack replacement

The lifetime of the plant is another essential input parameter to actualise the CAPEX. However, whereas the value choice of the other parameters is well documented, the latter is less discussed. Most of the papers agree on the same lifetime for the facility: twenty years [6; 20; 23; 37; 50; 62; 66]. Yet, some studies are more optimistic about Alkaline Electrolysis and consider a facility lifespan of thirty years [25; 34; 46]. As Alkaline Electrolysis is a more mature technology, I assume a longer lifespan of the plant than Polymer Electrolyte Membranes Electrolysis. I use thirty and twenty years of facility lifespan for Alkaline and Polymer Electrolyte Membranes Electrolysis.

While a facility can be operated for up to thirty years, the cell stacks of the electrolyser, converting electricity into hydrogen, have to be replaced several times during the lifespan of the plant. Few papers share the same assumptions regarding this component. In general, it is considered that Alkaline Electrolysis enjoys a longer cell stack lifetime than Polymer Electrolyte Membranes Electrolysis [20; 23; 25; 50]. [6] highlights that the lifespan range for Alkaline and Polymer Electrolyte Membranes Electrolysis is comparable, respectively 55,000-96,000 hours and 60,000-100,000 hours but that the latter suffers from higher efficiency degradation rate. To not complexify too much the model, I do not model the efficiency degradation rate but rather consider the different lifespan of cell stacks as it is commonly done in the literature. As [34], I consider three cell stack replacements for both technologies over the lifespan of the facility knowing that the cell stacks are expected to last between eight and fifteen years for Alkaline Electrolysis [6; 20; 23; 25; 50; 46; 62] and between five and nine years for Polymer Electrolyte Membranes Electrolysis [20; 23; 25].

The cost level of the cell stack replacement is generally expressed in terms of a percentage of the CAPEX. [68] consider a value of 40% for Alkaline Electrolysis. [34] evaluates the latter at respectively 30% and 40% for Alkaline Electrolysis and Polymer Electrolyte Membranes Electrolysis. [34] validates [50] as they both consider a higher value for Polymer Electrolyte

Membranes Electrolysis. I thus use [34]'s values, 30% and 40% of the CAPEX.

6.1.5 Electrolyser efficiency

The efficiency of the electrolysis process is generally expressed in the percentage of the High Heating Value process and is computed with the following equation [66]:

$$Efficiency = \frac{HHV}{Power\ consumption * \rho} \tag{7}$$

Where HHV is the Higher Heating Value of hydrogen, equal to 3.54 kWh/Nm^3, the *Power Consumption* expressed in [kWh/kgH_2] and ρ the density of hydrogen, equal to 0.0899 kg/Nm^3.

Among the literature, the estimation of the efficiency varies for both technologies. [62] summarises the current knowledge for Alkaline Electrolysis and specifies that cell stack efficiency and system efficiency should be differentiated. The latter includes also different losses that could occur while balancing the overall system. [6] evaluates the system efficiency of respectively Alkaline and Polymer Electrolyte Membranes Electrolysis between 60-70% and 54-71% of the HHV[4]. The last research, performed by [68], suggests an average system efficiency of 73 and 76% of HHV[5] for Alkaline and Polymer Electrolyte Membranes Electrolysis. These values respectively correspond to a power consumption of 54 and 52 kWh/kgH_2.

6.1.6 Flexibility

Besides the cost components, Alkaline and Polymer Electrolyte Membranes Electrolysis have also different technical features impacting the hydrogen production. The load flexibility is the load range where the electrolyser can produce hydrogen [6]. Alkaline Electrolysis has load flexibility between 20-100% of the nominal load while Polymer Electrolyte Membranes Electrolysis is much more flexible with a range between 0-100%. Besides these operating ranges, two different states exist: warm and cold.

6.1.6.1 Warm state

An electrolyser is in a warm state, or hot standby, if the electrolyser is shut down for less than eight hours in a row [34]. In a warm state, the electrolyser doesn't produce hydrogen but

[4] Values were originally expressed in % of Low Heating Values (LLV)
[5] Same remark

needs a shorter period to get back to the operating range. The conservation of the process in the warm states implies consumption of 39kW. 2kW are also required for safety reasons. In total, during a warm state, the electrolyser is consuming 41kW [21; 34]. In this master's thesis context, 41kW is minor compared to the 100MW capacity. To get back to the operating mode, Alkaline and Polymer Electrolyte Membranes Electrolysis respectively require between one and five minutes and a few seconds [34; 68].

6.1.6.2 Cold state

If the electrolyser is not operated for more than eight hours in a row, it is switched to cold standby. During this state, the electrolyser's power consumption amounts to 5kW on top of the 2kW needed for safe operations [21; 34]. To be brought back to the operation mode, Alkaline Electrolysis needs between one and two hours [34; 68]. During this ramp-up period, where the electrolyser is not producing hydrogen, the power consumption is set to 100% of the nominal load on top of the 2kW of safety. On its side, Polymer Electrolyte Membranes Electrolysis is much more flexible and only requires between one and five minutes to get back to full load operations [34; 68].

6.2 Storage

[23; 50; 62] demonstrate the economic effectiveness of adding large-scale underground storage to the facility. The latter provides more flexibility to adapt to power market conditions than metal tanks with smaller capacity. This type of storage is however available under specific geological conditions. Artificial hydrogen salt cavern is preferred and represents the best and cheapest option [10; 50]. The storage CAPEX is estimated at 18.70 $/kgH_2$ or 14.06 €/kgH_2[6]. As I consider an underground storage facility with a capacity of seven days of demand at full load, it represents a storage capacity of 320,000 kgH_2. Hence, the overall investment costs for the storage amount to 4,499,200 €.
[50] does not include OPEX in its analysis. Nevertheless, [62] includes a fixed component of the storage CAPEX as an approximation of yearly OPEX equal to 1.5% based on [24].

Furthermore, an additional consumption is required to compress the hydrogen. [68] also men-

[6]Value in $ converted in € by using the 2014 average exchange rate US dollars/euros provided by [63].

tions additional consumption of about 3 kWh/kgH_2 to compress hydrogen. [50] is more precise, by assessing them to 2.2 kWh/kgH_2 for underground storage.

6.3 Discount rate

Among the literature, the estimation of the discount rate in the techno-economic analyses is very disparate. Two methods exist and are detailed in the literature: either using the average discount rate of renewable projects in a specific geographic area [1; 34; 50; 68; 66] or computing the Weighted Average Cost of Capital (WACC) [37; 62]. That leads to a wide range of estimated values, from 3% [1] to 10.96% [62]. The average value of 7% will therefore be used further. For this parameter, a sensitivity analysis seems therefore necessary due to the lack of a common basis.

7 Bidding Strategy Model

In this section, I describe the day-ahead bidding strategy used to compute the power purchase costs, the main driver of the $OPEX_{var}$*. First of all, I list and justify the model's assumptions. Then, I state the parameters, variables, and constraints of the bidding strategy are displayed. The bidding strategy is derived and adapted from [34; 50].*

7.1 Assumptions

- I simulate one-year time horizon. The system starts with empty hydrogen stocks and no hydrogen stock can be reported to another period.

- A constant hourly demand is estimated. Every hour, I assume a constant hydrogen outflow to deliver to the market. All the hydrogen produced is also compressed [62]. The demand can be either met directly by the electrolyser and/or by the storage facility. The facility does not produce more hydrogen than required.

- I do not consider any degradation of the cell stack efficiency. I implement a constant efficiency but different lifespan for the cell stacks. I include the cell stack replacement costs in the $CAPEX$ dimension.

- Even though [62] shows that grid fees could play an important role in electrolyser's profitability, I do not consider them. The grid fee's regulation varies widely among European power markets and could therefore alter the assessment of the impact of market conditions on the Levelized Cost of Hydrogen.

- While I model both standby modes, I only model cold start-up for Alkaline Electrolysis for one hour. Because of the short reaction time of Polymer Electrolyte Membranes Electrolysis, it can be neglected for this technology. To switch to or to keep the cold standby mode, I also consider that a sufficient amount of hydrogen is present in the storage. I set the minimum storage limit to two hours of demand to take into account the ramp-up hour when no hydrogen can be produced.
  I do not model hot startups for both technologies as they both required a limited time. It does not greatly impact hydrogen production and power consumption.
  However, I model consumption during cold and hot standby.

- The water electrolysis facility sources only its power on the day-ahead market. The minimum bidding volume on this market is 100kWh in Europe. For smaller bids, i.e. safety consumption and consumption during hot/cold standby mode, electricity is sourced on the regulated market and bought at 100€/MWh [34].
- I assume that the individual minimum operating load is applied to the whole facility even though electrolysis facilities are constituted of multiple cell stacks. In other words, for Alkaline Electrolysis, the minimum operating load of the facility is 20%.
- I do not consider the cost of water for both technologies.
- I do not assume any revenue from the selling of the oxygen and the heat produced during the process.

7.2 Model

7.2.1 Sets

Sets	**Description**	**Value**
w	Water Electrolysis Technologies	{AEL, PEML}
d	Days in a Year	{1...365}
h	Hours in a Day	{1...24}
s	Price Scenario	{2017, 2020, 2021}
b	Bidding Zone	{BE, DK1, NO2}

Table 5: Sets

7.2.2 Parameters

Parameter	AEL	PEMEL	Symbol
Electrolyser capacity [kW]	100,000	100,000	$Cap\ Elec$
Electrolyser and compressor CAPEX [€/kW]	420	290	$KElec_w$
Install factor and indirect costs [% of CAPEX]	24.1%	24.1%	K_{Inst}
Electrolyser $\text{OPEX}_{\text{fixed}}$ [% of CAPEX]	13,1%	13,1%	O_{Elec}
Storage maximum capacity [kgH_2]	320,000	320,000	$StorMax$
Storage minimum capacity [kgH_2]	0	0	$Stor\ Ma$
Storage CAPEX [€/kgH_2]	14.06	14.06	K_{Stor}
Storage OPEX [% of Storage CAPEX]	1.5%	1.5 %	O_{Stor}
Lifespan of the facility [years]	30	20	n_w
Number of cell stack replacements	3	3	c
Value of the CAPEX per cell stack replacement	30%	40%	$Replace_w$
Power Consumption [kWh/kgH_2]	54	52	$PCons\ Elec_w$
Compressor Consumption [kWh/kgH_2]	2.2	2.2	$PCons\ Comp$
Minimal Operating Load [% of the nominal capacity]	20%	0%	$LoadMin_w$
Hot startup time	1-5min	<10seconds	/
Hot state consumption [kWh]	39	39	$HotCons$
Cold startup time	1 hour	1-5min	/
Cold state consumption [kWh]	5	5	$ColdCons$
Safety operations consumption [kWh]	2	2	$SafeCons$
Discount factor [%]	7	7	i
Capacity factor [% of the maximum load]	/	/	CF_w
Hourly Demand [kgH_2]	/	/	$HDemand$
Day-ahead power price [€/MWh]	/	/	$DA\ Price_{s,b,d,h}$
Regulated power price [€/MWh]	100	100	$Reg\ Price$

Table 6: Parameters

7.2.3 Variables

Variable	Description	Type
$DInv_{s,w,d,b,h}$	H_2 demand [kgH_2] placed on inventory on day d and hour h under price scenario s for technology w	continuous
$RDem_{s,w,b,d,h}$	Remaining annual demand of H_2 [kgH_2] to be satisfied by the facility under on day d and hour h under price scenario s for technology w	continuous
$Prod\ In_{s,w,b,d,h}$	H_2 production [kgH_2] made by the electrolyser on day d and hour h under price scenario s for technology w	continuous
$Stor_{s,w,b,d,h}$	H_2 in the underground storage [kgH_2] on day d and hour h under price scenario s for technology w	continuous
$Prod\ Out_{s,w,b,d,h}$	H_2 [kgH_2] delivered to the market on day d and hour h under price scenario s for technology w	continuous
$Power\ Cons_{s,w,b,d,h}$	Power consumption of the electrolyser [kWh] on day d and hour h under price scenario s for technology w	continuous
$Hot\ Sb_{s,w,b,d,h}$	$\begin{cases} 0, & \text{if the electrolyser is in hot standby on day } d \text{ and hour } h \text{ under price scenario } s \text{ for technology } w \\ 1, & \text{otherwise} \end{cases}$	binary
$Cold\ Sb_{s,w,d,h}$	$\begin{cases} 0, & \text{if the electrolyser is in cold standby on day } d \text{ and hour } h \text{ under price scenario } s \text{ for technology } w \\ 1, & \text{otherwise} \end{cases}$	binary

Table 7: Variables

7.3 Bidding strategy algorithm

Figure 17 presents the bidding strategy used to compute the electricity costs in $Power\ Cost_{s,w,b}$ for Alkaline Electrolysis[7]. I derive this strategy by adapting and combining [34; 50] works. I apply the following procedure every year of the scenarios.

7.3.1 Estimation of the capacity factor

I consider a fixed demand of hydrogen [kgH_2] per hour. This demand is assumed to be predictable and known by the water electrolysis facility. From this hourly demand, I derive an overall annual demand. I then determine the capacity factor, i.e. the percentage of operating hours in a year, through the following formula [50]:

$$CF_w = \frac{HDemand}{\frac{Cap\ Elc}{PCons\ Elec_w}} \tag{8}$$

[7] As mentioned in the assumptions, PEMEL does not consider cold start up time. Therefore, all the roots where the production is set to 0 and the power consumption to its maximum level are removed. Otherwise, the diagram remains identical.

7.3.2 Estimation of the power price threshold

Optimising the day-ahead biddings is equivalent to fixing a power price threshold under which the electricity should be bought. If the forecasted power price is under it, the facility is operated at its maximum possible output [34; 46; 47; 50]. This power price threshold is computed based on the capacity factor and the one-year historical load duration curve. The one-year historical prices are sorted out from the cheapest to the most expensive. The price observation, corresponding to the computed capacity factor, is used as the electricity price threshold. As the facility operates in a day-ahead market, this threshold is valid for the next twenty-four hours. The value is then recomputed based on new observations every day before the Gate Closure (12:00:00 CET).

7.3.3 Maximum allowed quantity in storage

Because of the assumption specifying that the facility shouldn't produce more than the annual demand, I create a variable $DInv_{s,w,b,d,h}$ [50]. The latter sets up the maximum demand placed for inventory and ensures that no extra production is made at the end of the time horizon.

$$DInv_{s,w,b,d,h} = \max\left(\min\left(Stor\ Max, RDem_{s,w,b,d,h} - \frac{MinLoad_w * Cap\ Elec}{PCons\ Elec_w}\right), 0\right) \tag{9}$$

7.3.4 Optimisation algorithm

Now that these parameters have been computed, I can enter the decision tree to determine the production quantity. The root I firstly enter depends on if either the forecasted price is above or under the threshold value.

7.3.4.1 Forecasted price smaller than the threshold value

In this case, the facility is setting its hydrogen production to its maximum possible level. If the electrolyser was not in a cold state in the previous hour, the hydrogen production by the electrolyser, $Prod\ In_{s,w,b,d,h}$, is set to:

$$\begin{aligned} &Prod\ In_{s,w,b,d,h} \\ &= \min\left(\max\left(DInv_{s,w,b,d,h} - Stor_{s,w,b,d,h-1} + Prod\ Out_{s,w,v,d,h}, \frac{MinLoad_w * Cap\ Elec}{PCons\ Elec_w}\right), \frac{Cap\ Elec}{PCons\ Elec_w}\right) \end{aligned} \tag{10}$$

Otherwise, if the facility was in a cold state previously, the electrolyser needs one hour of ramp-up to reach back its production state. During this hour, $Prod\ In_{s,w,b,d,h}$ is set to zero and the power consumption to its maximum level.

7.3.4.2 Forecasted price higher than the threshold value

The overall objective of this case is to produce the minimum quantity to minimise electricity cost. However, the electrolyser might be forced to produce to meet the hydrogen demand.
The first step is to compute the theoretical production necessary to fulfill the demand:

$$Prod\ In_{s,w,b,d,h} = \max\left(\min\left(Stor\ Min - Stor_{s,w,b,d,h-1} + Prod\ Out_{s,w,b,d,h}, \frac{Cap\ Elec}{PCons\ Elec_w}\right)\frac{MinLoad_w * Cap\ Elec}{PCons\ Elec_w}\right) \tag{11}$$

However, for Alkaline Electrolysis, it exists a minimum load, under which the electrolyser is not producing anything and must switch to standby.
If the theoretical value is above the load threshold and if the system was not in a cold state the previous period, then the production is set to the previous theoretical value computed.
On the opposite, if the system was in a cold state previously, the electrolyser needs to ramp up: the production is set to zero and the power consumption to its maximum level. This situation could happen if the electrolyser has no necessary storage to fulfill the demand

If the theoretical value is under the load threshold, then I have to check if the storage is sufficient to switch to a standby state. I consider that at least two hours of demand must be present in the storage facility to switch/keep the standby mode. If the system was on standby for more than eight hours in a row, the facility switches to a cold state [34]. If the storage is not sufficient, I set the production and the power consumption to their minimum operating load level.

After each hour, the storage levels and the power consumption of the electrolyser are computed:

$$Stor_{s,w,b,d,h} = Stor_{s,w,b,d,h-1} + Prod\ In_{s,w,b,d,h} - Prod\ Out_{s,w,b,d,h} \tag{12}$$

$$Power\ Cons_{s,w,b,d,h} = Prod\ In_{s,w,b,d,h} * (PCons\ Elec_w + PCons\ Comp) \tag{13}$$

The consumption of the compressor, $PCons\ Comp$ is added to the overall power consumption.

7.4 Levelized Cost of Hydrogen computation

Now that all the components are ready, I compute the Levelized Cost of Hydrogen. The power costs are computed with the following formula. Recall that the safety consumption and the consumption during standby modes are sourced on the regulated market as suggested by [34]. The electricity prices are divided by 1000 as they are orginally expressed in €/MWh while the power consumption is expressed in kWh

$$Power\ Cost_{s,w,b} = \sum_{d \in D} \sum_{h \in H} Power\ Cons_{s,w,b,d,h} * \frac{DA\ Price_{s,b,d,h}}{1000} + \frac{Reg\ Price}{1000} * \left(8760 * SafeCons + \sum_{d \in D} \sum_{h \in H} Hot\ Sb_{s,w,b,h} * HotCons + Cold\ Sb_{s,w,b,h} * ColdCons \right) \tag{14}$$

I can now compute other dimensions of the Levelized Cost of Hydrogen. These dimensions only depend on the technology used. The $CAPEX\ Base_w$ is firstly computed. The latter includes the CAPEX for the electrolyser and the compressor for the total capacity.

$$CAPEX\ Base_w = KElec_w * Cap\ Elec \tag{15}$$

Then, I compute the component related to installation and indirect costs, $CAPEX\ Inst_w$.

$$CAPEX\ Inst_w = CAPEX\ Base_w * K_{Inst} \tag{16}$$

The last dimension of the CAPEX for the electrolyser, $CAPEX\ Replace_w$, linked to the replacement of the cell stack, is calculated.

$$CAPEX\ Replace_w = CAPEX\ Base_w * Replace_w * c \tag{17}$$

The electrolysis facility has also underground storage, implying $CAPEX\ Stor$, independent of the electrolysis technology.

$$CAPEX\ Stor = K_{Stor} * StorMax \tag{18}$$

Finally, I compute the $OPEX\ fix_w$ for the electrolyser, the compressor, and the underground storage:

$$OPEX\ fix_w = CAPEX\ Base_w * O_{Elec} + CAPEX\ Stor * O_{Stor} \tag{19}$$

The Levelized Cost of Hydrogen for a technology w, in a bidding zone b and the price scenario s, $LCOH_{s,w,b}$, is, as stated by equation 2:

$$LCOH_{s,w,b} = \frac{(CAPEX\ Base_w + CAPEX\ Inst_w + CAPEX\ Replace_w + CAPEX\ Stor) * \frac{i*(1+i)^n}{(1+i)^n - 1} + OPEX\ fix_w + Power\ Cost_{s,w,b}}{HDemand * 8760} \tag{20}$$

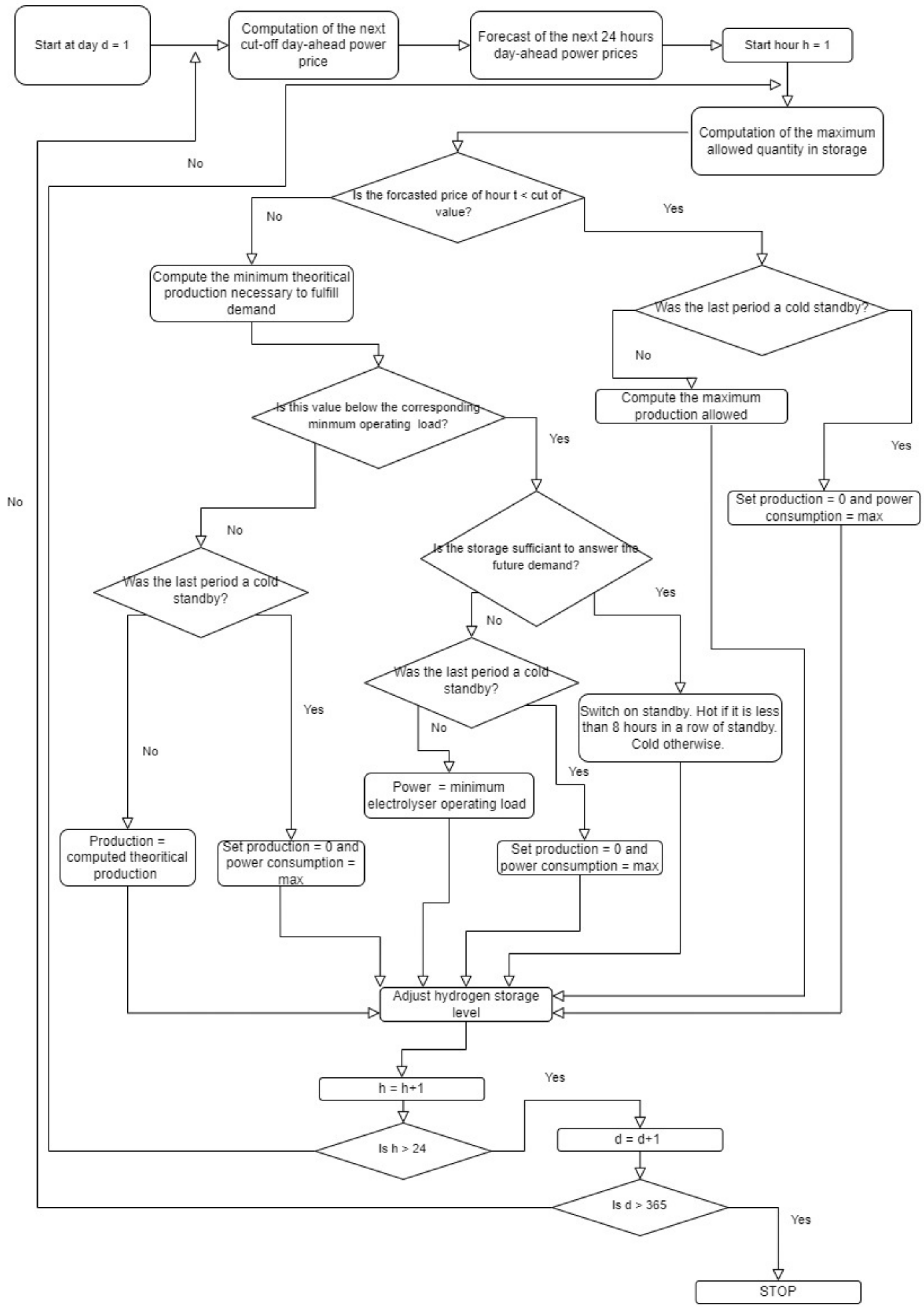

Figure 17: AEL Bidding Strategy diagram

8 Results and discussion

Based on the computation of the Levelized Cost of Hydrogen detailed in the Section 7.4 and on the modeled bidding strategy, I build the following results. I focus on 4 price scenarios covering 3 bidding zones as highlighted in Section 4.1: 2021 HPHV (BE-NO2-DK1), 2020 LPLV (BE-NO2), 2020 LPHV (DK1), and 2017 IPV (BE-NO2-DK1).

8.1 Market conditions

The major stake of this master's thesis is to analyse the impact of market conditions on the profitability of water electrolysis in Europe. *Figure 18* displays the evolution of the Levelized Cost of Hydrogen (LCOH) with the capacity factor, i.e the hydrogen demand, under different price scenarios. These results are built under the assumption of "Crystal Ball", a perfect forecast of future day-ahead prices. As a reminder, I derive the capacity factor from a hydrogen demand that is assumed to be known. The evolution of the capacity factor in *Figure 18* can then be seen as an evolution of the hydrogen demand: a higher demand implies a higher capacity factor. I start the analysis at a capacity factor of 40% due to the importance of a sufficient number of operating hours [34; 66].
In *Figure 18*, I also plot the levels of the Levelized Cost of Hydrogen from Steam Methane Reforming (SMR) and Steam Methane Reforming with Carbon Capture and Storage technology (SMR+CCS). I derive these values from [44; 50][8]. The Levelized Cost of Hydrogen values from Steam Methane Reforming with and without Carbon Capture and Storage must be considered indicative. They are not computed with the same methodology used in this master's thesis and therefore do not take into account natural gas and Emission Trading System market conditions these years.

These graphs can be analysed from two angles. On the one hand, they can be assessed by comparing the two technologies. A striking element is the difference in Levelized Cost of Hydrogen curves' slopes between the two technologies. Alkaline Electrolysis (AEL) has a more important decreasing rate than Polymer Electrolyte Membranes Electrolysis (PEMEL). This difference is due to the modeling of cold start-ups for Alkaline Electrolysis. The difference can

[8]The data are orginally in US dollars. I convert them to euros at an exchange rate of 1\$ = 0.95€ [15]

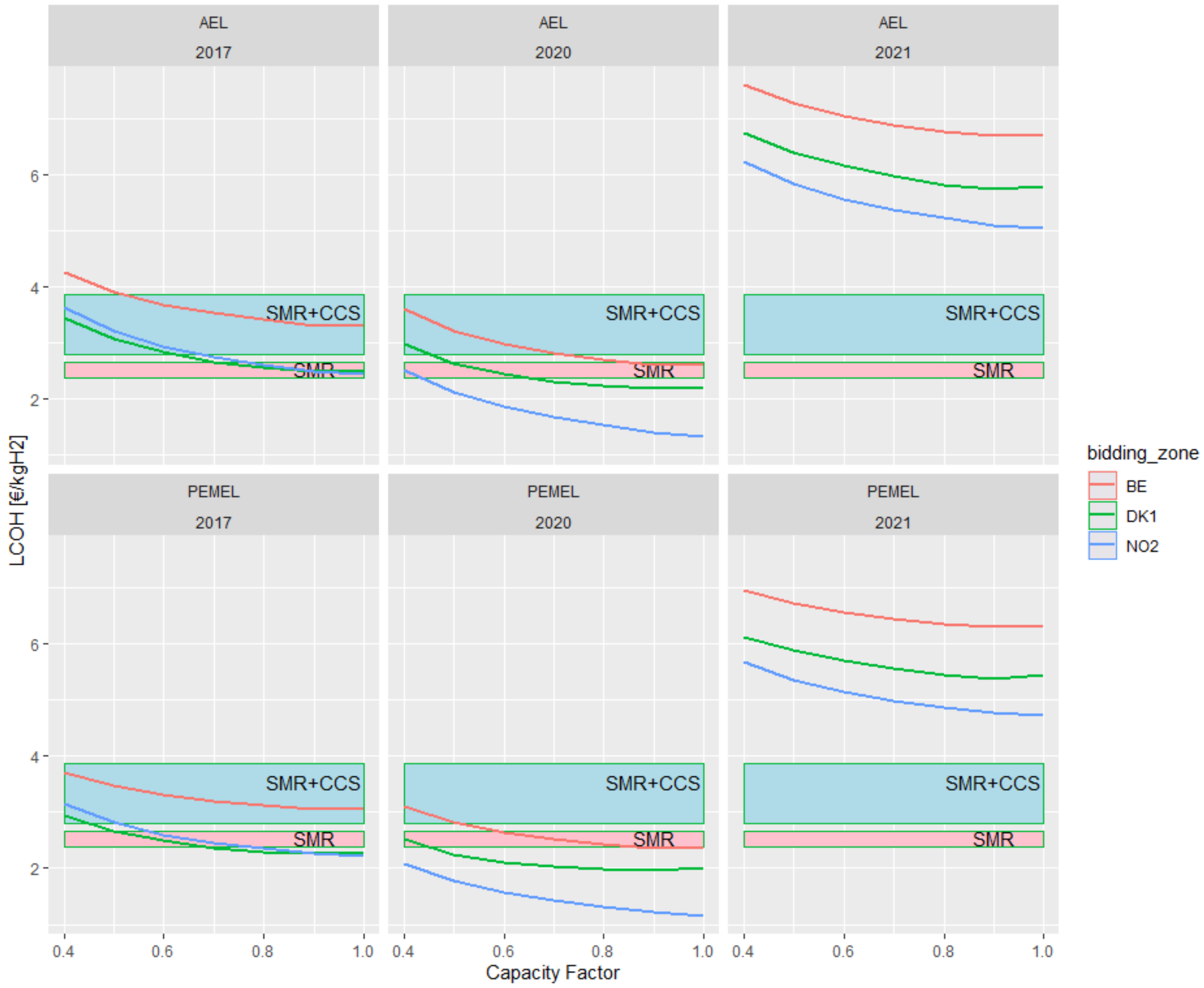

Figure 18: Evolution of the Levelized Cost of Hydrogen

be mainly observed at the low capacity factor as, at higher levels, the electrolyser is doing a few cold start-ups. Afterward, Polymer Electrolyte Membranes Electrolysis has a lower Levelized Cost of Hydrogen independent of the market conditions and the bidding area. The longer lifespan of the facility is thus not sufficient to compensate for higher CAPEX and higher power consumption.

On the other hand, I derive observations based on the price scenarios. Under the IPV scenario (2017), Western Denmark is more profitable than Southern Norway at a capacity factor below 80%. This suggests that, even if price levels are higher in Western Denmark, the electrolyser manages to access lower price periods. In practice, mean average day-ahead prices are comparable (30 and 28 €/MWh for Western Denmark and Southern Norway), but their variabilities are considerably different (21 and 6 €/MWh for Western Denmark and Southern Norway). At comparable mean price levels, a higher variability is therefore beneficial for water electrolysis. For both technologies, Belgium would be competitive with Steam Methane Reforming with Carbon Capture and Storage technology (SMR+CCS). On their side, Alkaline and Polymer Electrolyte Membrane Electrolysis would be competing with Steam Methane Reforming (SMR) above a capacity factor of 80 and 60%.

Under the most profitable conditions, the LPLV and LPHV scenarios (2020), the overall Levelized Cost of Hydrogen levels decrease. This time, Southern Norway is more profitable than Western Denmark. It can be explained as the mean prices are significantly different: 25 €/MWh (DK1) and 9 €/MWh (NO2). The high volatility of Western Denmark is not sufficient to overcome Southern Norway. The conditions offered by LPLV and LPHV scenarios would allow water electrolysis to out-perform usual levels of Steam Methane Reforming's Levelized Cost of Hydrogen in Southern Norway and Western Denmark.

Under the worst market conditions, the HPHV scenario (2021), the impact of the rising in prices and volatility in 2021 increases the Levelized Cost of Hydrogen. In every bidding zones, their levels make water electrolysis non-competitive when compared to the reference values of its competitors. The Levelized Cost of Hydrogen is roughly doubled for every bidding zone compared to the IPV scenario.

Furthermore, under all the scenarios, Belgium displays the highest Levelized Cost of Hydrogen. It comforts the intuition that low prices are essential to achieving a profitable water electrolysis facility. A high variability only helps the facility when the mean prices are comparable and when the capacity factor is low.

Concerning the optimal capacity factor for a water electrolysis facility, I focus the analysis on *Figure 19*. It displays the Levelized Cost of Hydrogen in 2020 under the "Crystal Ball" assumption for Alkaline Electrolysis. The curves' behaviours are similar to the other scenarios and technologies. Confirming [23; 34; 66] intuitions, the capacity factor must be high enough to cover the investment expenses. As [50], Belgium and Western Denmark reach the optimal capacity factor at 90% under every price scenario. For Southern Norway, an improvement is obtained when the capacity factor is pushed to 100%. Operating the electrolyser at full load without optimisation is thus more profitable. In practice, it means that the gain on the ratio $\frac{CAPEX}{Hydrogen\ Produced}$ when moving from a capacity factor of 90% to 100% is higher than the loss made on the ratio $\frac{Power\ Costs}{Hydrogen\ Produced}$.

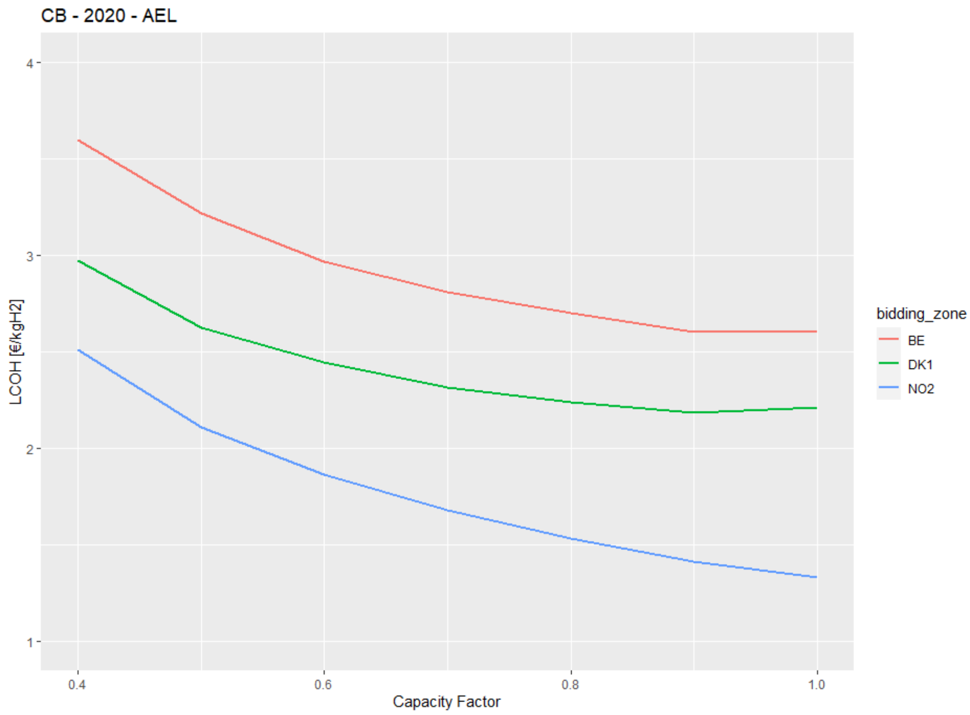

Figure 19: Levelized Cost of Hydrogen evolution

8.2 Technologies assessment

Now that the differences between the market areas and scenarios have been highlighted, this section focuses on the economic performance of water electrolysis technologies.

8.2.1 Levelized Cost of Hydrogen comparison

Alkaline and Polymer Electrolyte Membranes Electrolysis differ by several components as shown in *Table 6*. The biggest one concerns flexibility. Alkaline Electrolysis requires one hour of a cold start-up while Polymer Electrolyte Membranes Electrolysis does not. These features impact the Levelized Cost of Hydrogen computation through both the CAPEX dimension and the modeling of the bidding strategy. *Figure 18* demonstrates that Polymer Electrolyte Membranes Electrolysis (PEMEL) is cheaper than Alkaline Electrolysis (AEL). To better assess the differences between the two technologies, $Diff_{s,b}$ is computed. This new variable represents the savings in the Levelized Cost of Hydrogen in % achieved by Polymer Electrolyte Membranes compared to Alkaline Electrolysis.

$$Diff_{s,b} = \left(\frac{LCOH_{s,AEL,b} - LCOH_{s,PEMEL,b}}{LCOH_{s,PEMEL,b}} \right) * 100 \tag{21}$$

Figure 20 plots the evolution of the difference [%] of the Levelized Cost of Hydrogen between the 2 technologies ($Diff_{s,b}$) under the "Crystal-Ball" assumption at a capacity factor of 90%. *Figure 20* shows that $Diff_{s,b}$ is changing given the price scenario and the market area. It implies influences of the power market conditions.

Figure 20: Difference [%] in the Levelized Cost of Hydrogen between AEL and PEMEL

For every bidding zones, the highest performance of the Polymer Electrolyte Membranes Electrolysis compared to Alkaline Electrolysis is achieved under the LPLV scenario. This is particularly true for Southern Norway where the Levelized Cost of Hydrogen is 16.4% lower than Alkaline Electrolysis. This result suggests that, on one hand, Polymer Electrolyte Membranes Electrolysis is more capable than Alkaline Electrolysis to take advantage of the lower price periods. On the other hand, the LPLV scenario offers the lowest *Power Cost*. Therefore, the impact of the Alkaline's cold start-up cost is more important under this scenario than under others. Once again, under the IPV scenario (2017), Western Denmark and Southern

Norway are behaving similarly. Finally, the difference between the two technologies and the gap between the market areas are the smallest under the HPHV scenario.

8.2.2 Levelized Cost of Hydrogen breakdown

A breakdown of the Levelized Cost of Hydrogen under every price scenario and bidding area is set up. In *Figure 21*, I consider a capacity factor of 0.9 and perfect forecasts of future electricity prices (Crystal Ball).

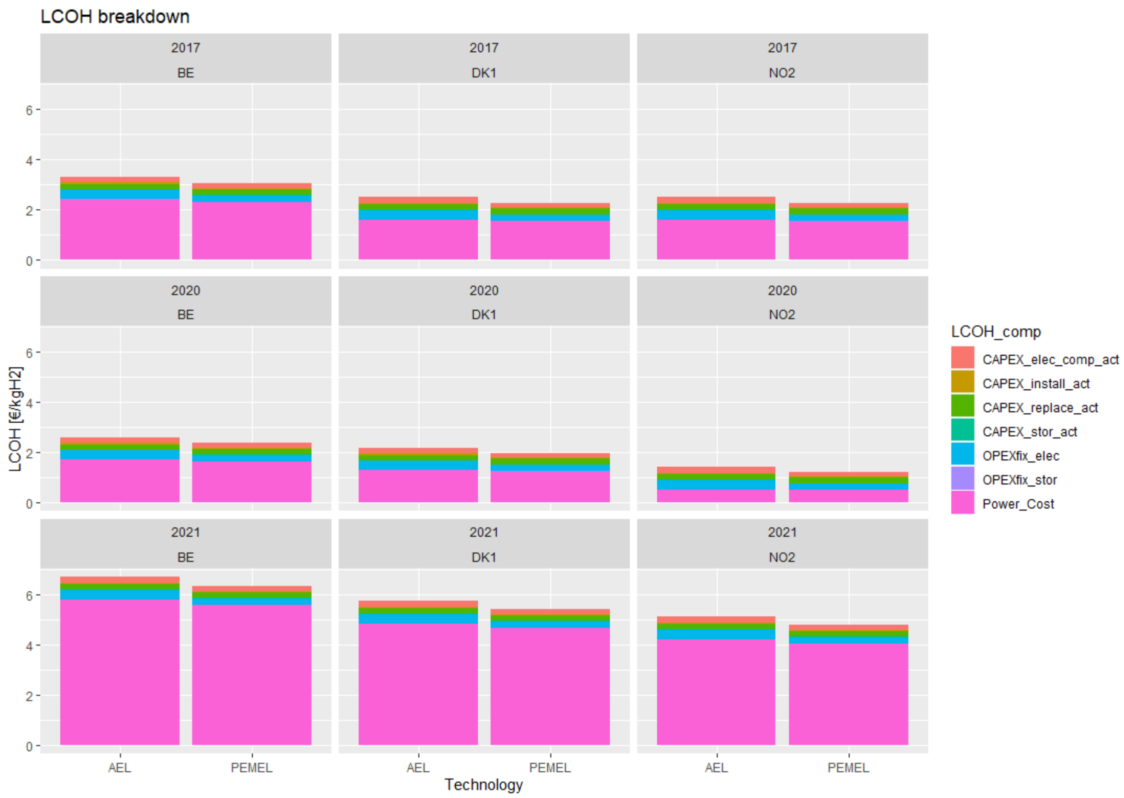

Figure 21: Levelized Cost of Hydrogen breakdown

Figure 21 highlights *Power Cost* dominance in the share of the Levelized Cost of Hydrogen. Under the 2021 HPHV scenario, the Levelized Cost of Hydrogen skyrockets in every bidding zone because of the increased *Power Cost*.

Figure 22 explains the decreasing trend of Southern Norway between a capacity factor of 0.9 and 1 under the 2020 LPLV scenario in *Figure 18*. The share of *Power Cost* is consider-

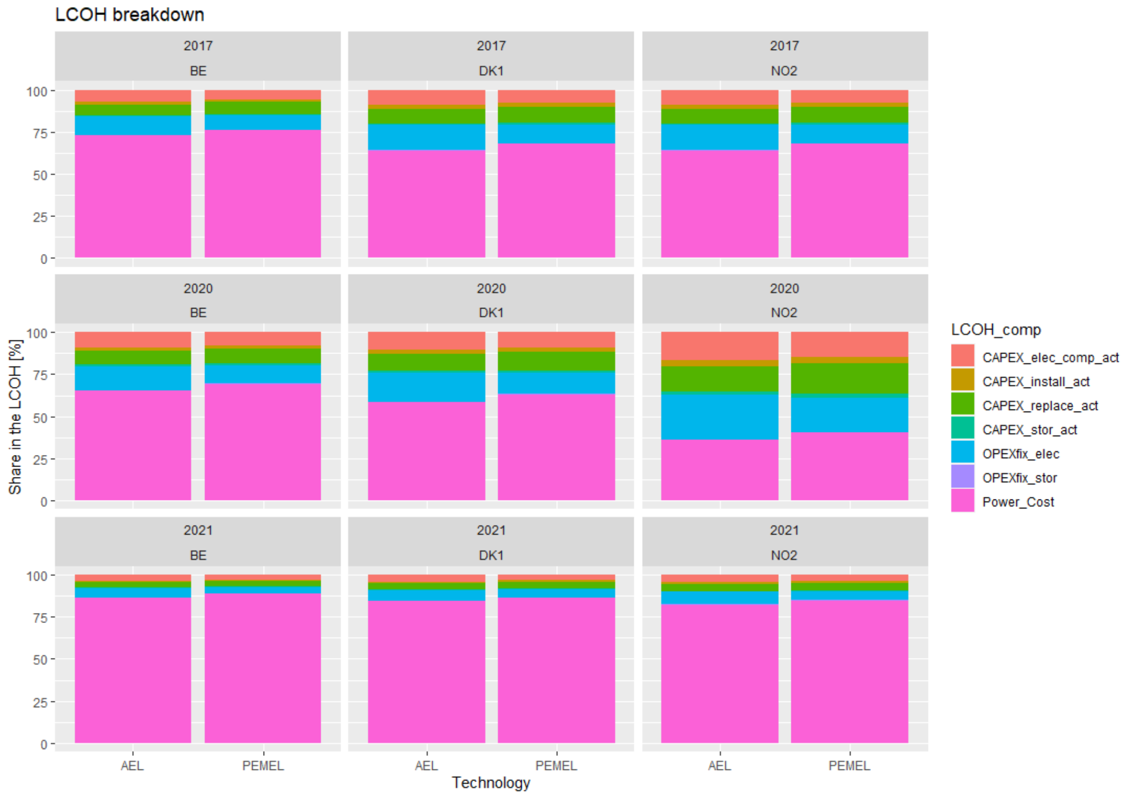

Figure 22: Cost breakdown expressed in % of the Levelized Cost of Hydrogen

ably smaller than in other market areas. It explains why the water electrolysis facility has an interest to push production to its maximum level.

Furthermore, the share of *Power Cost* in the Levelized Cost of Hydrogen is higher for Polymer Electrolyte Membranes Electrolysis than for Alkaline Electrolysis. The lower CAPEX caused by the scaling-up effect can explain this occurence.

Overall, all expenses related to storage are minimal while the main part of the Levelized Cost of Hydrogen is constituted of *Power Cost* and CAPEX electrolyser costs.

8.3 Electricity price forecasting impacts

Results Sections 8.1 and 8.2 are obtained under the "Crystal Ball" assumption. However, a perfect knowledge of future day-ahead prices is not realistic when a water electrolysis facility is bidding on the day-ahead market.

In practice, market participants are using forecasts to schedule their consumption. Forecasting errors can potentially conduct to higher *Power Cost* and thus imply a higher Levelized Cost of Hydrogen. Thanks to the simulations performed in Section 5, I can compute the impact of the forecasting errors on the Levelized Cost of Hydrogen. Whereas the decision to operate or not to operate the electrolyser is based on the forecasts, *Power Cost* is computed based on the actual market-clearing price. *Figure 23* exhibits the impact of using forecasts in the

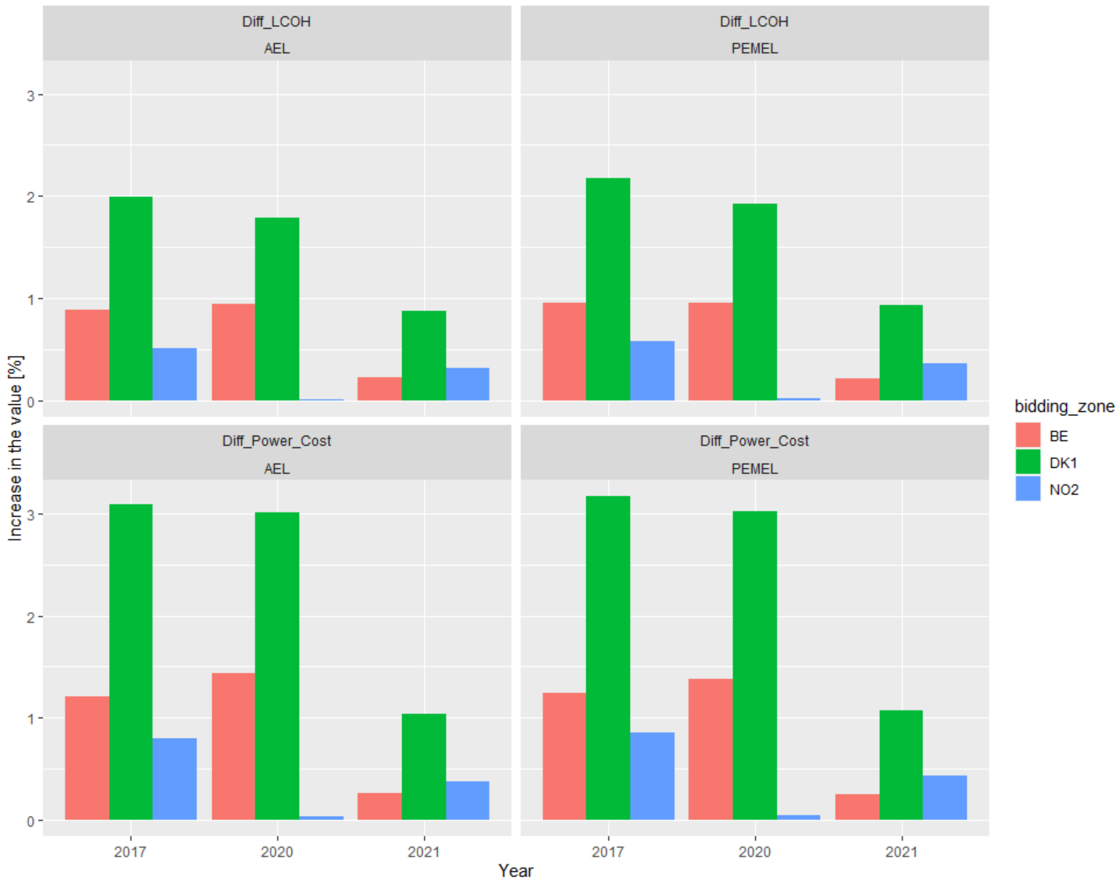

Figure 23: Increase in the Levelized Cost of Hydrogen and in the Power Cost [%] caused by forecasts

bidding strategy for both technologies under the different price scenarios and bidding zones at a capacity factor of 90%. The impacts on the *Power Cost* are higher than the impact on the Levelized Cost of Hydrogen. Overall, Polymer Electrolyte Membranes are more affected than Alkaline Electrolysis. This can be linked to the higher share of power costs in the Levelized Cost of Hydrogen displayed in *Figure 22*.

The global impact of forecasting on the Levelized Cost of Hydrogen is small. With a range located between 0.04 and 2.17%, the impact on the profitability metrics amounts to a few cents per kgH_2. This limited impact should be nuanced and can be explained by the modeling strategy assumptions. The strategy does not aim to optimise production on a multi-period horizon. The model rather takes a decision hour per hour based on historical data. As shown in *Figure 15* Fourier terms successfully manage to forecast spikes' timing, giving them a good chance of being on the same side of the price threshold as the Crystal Ball case.

The market area the most impacted by the introduction of the forecast is Western Denmark where the effect is doubled compared to other areas. Belgium could have been expected to achieve such results as, in Section 4.1, this bidding zone is described as the one subject to the highest variability. Even if the maximum difference Δ is a good metric of variability for the arbitrage cases, it is less pertinent when it comes to assessing price variations within a time horizon and potential forecast performances.

A striking element is the relative position of the price scenarios. While the 2021 HPHV scenario was showing the worst performance of the forecasts (MAE - Section 5), the impact of the introduction of the forecasts is the lowest among the studied scenarios. These results demonstrate the limits of using MAE as a metric to assess forecasts' performances.

8.4 Sensitivity analysis

Section 6 shows the importance of the parameters' estimation on the Levelized Cost of Hydrogen and also displays the divergence among the literature on these parameters' values. Performing a sensitivity analysis is therefore essential to better understand to impact of every estimation on the final computation. For every key parameter, the impact of increasing their value by 25% is assessed on the Levelized Cost of Hydrogen. Only the results for Western Denmark using forecasted prices at a capacity factor of 90% are displayed in *Figure 24*. Other market areas and scenarios present fairly comparable results. Detailed results can be found in Appendix K.

The two parameters impacting the Levelized Cost of Hydrogen the most are the $PCons\ Elec_w$, the power consumption of the electrolyser for a technology w, and $KElec_w$, the CAPEX for the electrolyser of technology w and the compressor. A nearly linear relationship between

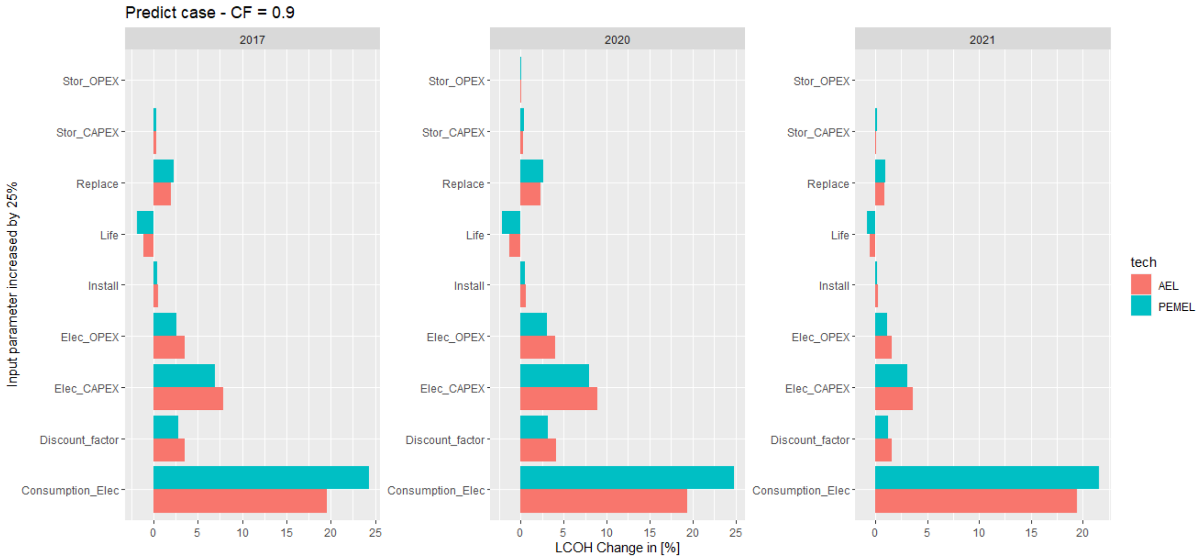

Figure 24: Sensitivity for DK1 using Forecasted prices at a Capacity Factor of 0.9

$PCons\ Elec_w$ and the Levelized Cost of Hydrogen can even be observed for Polymer Electrolyte Membranes. This is due to the high share of *Power Cost* in the structure Levelized Cost of Hydrogen. This relationship is also present to a lesser extent for Alkaline Technology. Cold startups, required when switching from cold standby to operational mode, imply additional costs in the power bill. Investing in research and development to reduce both the power consumption and the CAPEX of the electrolyser is thus crucial to produce cheaper electricity-based hydrogen.

The longer lifespan n of the facility is the only increased parameter than can reduce the Levelized Cost of Hydrogen. The impact of the discount rate r is however more important in the actualisation part of the Levelized Cost of Hydrogen formula. The small impact of storage on the overall cost structure is also to notice as previously.

9 Limitations and future research

This master's thesis has contributed to an alternative approach of the Levelized Cost of Hydrogen computation to emphasise the impact of day-ahead power market conditions in the optimisation of day-ahead bidding schedule. Nevertheless, the research of the analysed topic comprises some limitations. They can be summarised around three dimensions the scope, the model, the comparability and pose avenues for future research.

While this master's thesis gives water electrolysis investors a broad view of the power market conditions in Europe, the analysis is limited to the day-ahead market to keep a realistic scope. In reality, water electrolysis facilities have many other possibilities to source their power consumption (Section 3.2). However, other power market mechanisms in Europe displays significant differences in their design and make a European comparison difficult. In this analysis, I demonstrate that Southern Norway and Western Denmark are appealing market areas regarding the day-ahead market. Further research could then focus on one of these bidding zones and combine day-ahead optimisation with other power market dimensions (future market, intraday market, imbalance settlement, and ancillary services). Furthermore, only European bidding zones are considered in this master's thesis. Nevertheless, Europe could import hydrogen or hydrogen derivatives from non-European markets. Therefore, countries with a large availability of Variable Renewable Energy Sources deserve interest from researchers. To analyse the delivery of hydrogen to Europe, scholar could therefore focus on transportation and associated costs of hydrogen into the European market.

The bidding strategy detailed in Section 7 has the major advantage of being simple to compute. The day-ahead optimisation takes decisions based on a hourly demand. This model leads to a small impact of day-ahead price forecasts on the Levelized Cost of Hydrogen. In practice, water electrolysis facilities may be able to supply a hydrogen demand for a longer period (daily, weekly). This element gives room for a multi-period optimisation. As the impact of forecasts on such optimisation might be completely different, future research could aim to evaluate the savings made on a longer period optimisation and the influence of forecasts on the latter.

Finally, in Section 8.1, I compare the Levelized Cost of Hydrogen from water electrolysis with the conventional values of Steam Methane Reforming with and without Carbon Capture and Storage technologies. I specify that this comparison should remain indicative as the Steam Methane Reforming values are not computed with the same methodology and the same focus on market conditions. Therefore, I would like to encourage other researchers to apply this methodology to Steam Methane Reforming. The resulting research could then determine the impact of of natural gas and Emission Trading System prices on the Levelized Cost of Hydrogen of Steam Methane Reforming. Additionally, this research may help in determining the impact of market conditions on investments in water electrolysis.

10 Conclusion

The European Commission and its state members consider that water electrolysis will play an important role in the decarbonisation of hydrogen production and the energy transition. However, its cost structure still prevents it to be developed at a large scale. One way to improve water electrolysis' profitability is to optimise day-ahead biddings to source the power consumption. The Levelized Cost of Hydrogen is often used in the literature to assess the competitiveness in hydrogen production. Usually, the Levelized Cost of Hydrogen is defined as the net present value of the lifetime costs divided by the net present value of the hydrogen production. Yet, the prediction of future costs is becoming more and more challenging given the uncertainty placed on power markets, the main cost driver of water electrolysis. Therefore, this study takes an alternative definition of the metric. This master's thesis aims to highlight the impact of day-ahead market conditions on the Levelized Cost of Hydrogen for Alkaline and Polymer Electrolyte Membranes Electrolysis while optimising day-ahead biddings.

Four price scenarios in three European bidding zones are derived from historical data. These scenarios present all significant differences and appealing features for the development of water electrolysis. The scenarios are: Low Price Low Variability (LPLV 2020) in Belgium and Southern Norway; Low Price High variability (LPHV 2020) in Western Denmark; Intermediate Price and Variability (IPV 2017) in Belgium, Western Denmark, and Southern Norway; High Price and High Variability (HPHV 2021) in Belgium, Western Denmark, and Southern Norway. These scenarios allow us to draw potential pathways that power markets could take in the future and to assess the Levelized Cost of Hydrogen related to water electrolysis.

In this document, I model a case study to answer to raised questions. This case study covers day-ahead optimisation for an Alkaline and Polymer Electrolyte Membranes Electrolysis facility equipped with underground hydrogen storage under the four different price scenarios. In line with other results in the literature, this master's thesis highlights that low prices are crucial for water electrolysis' profitability. The LPLV 2020 appears to be the most profitable scenario for every bidding zones studied. In the IPV 2017 scenario, Western Denmark is displaying equivalent mean day-ahead price and significantly higher variability than Southern Norway. At a facility capacity factor lower than 80%, Western Denmark is outperforming the Norwegian bidding zone. It highlights that, at equivalent prices, high variability is profitable for electrolyser's business models. The HPHV 2021 scenario represents the worst possible future direction of power markets. The high power prices double the Levelized Cost of Hydrogen for every bidding zone compared to the IPV 2017 scenario.

Furthermore, the day-ahead market conditions also impact the optimal capacity factor for a water electrolysis facility. While in Belgium and Western Denmark, a Power-to-Gas plant has an interest to operate at 90% of the total load. This remaining capacity gives room for flexible operations in the day-ahead market. In Southern Norway, power costs account for a smaller share of the total Levelized Cost of Hydrogen. An electrolyser should, therefore, operate at full load to reduce the impact of initial investments on the cost structure.

This master's thesis also highlights the differences between the Levelized Cost of Hydrogen from Alkaline and Polymer Electrolyte Membranes Electrolysis. It appears that Polymer Electrolyte Membranes Electrolysis is proven to be more cost-efficient than Alkaline Electrolysis under all price scenarios. Polymer Electrolyte Membranes Electrolysis benefits from a higher scaling-up effect reducing its CAPEX. Moreover, this technology has an operational load from 0 to 100%. It allows Polymer Electrolyte Membrane Electrolysis to not suffer from start-up costs and to better exploit price fluctuations. These elements combined with a higher efficiency reduce the power bill compared to Alkaline Electrolysis.

The introduction of day-ahead price forecasts in my model does not significantly influence the Levelized Cost of Hydrogen. The ARIMA model used to forecast day-ahead prices is successfully predicting price spikes timing. This gives a good chance to the model to achieve comparable results to the "Crystal ball" assumption.

Finally, the two parameters impact the water electrolysis' profitability more are electrolyser's power consumption and CAPEX. The storage dimension is not significantly impacting the Levelized Cost of Hydrogen.

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A Day-ahead prices boxplots

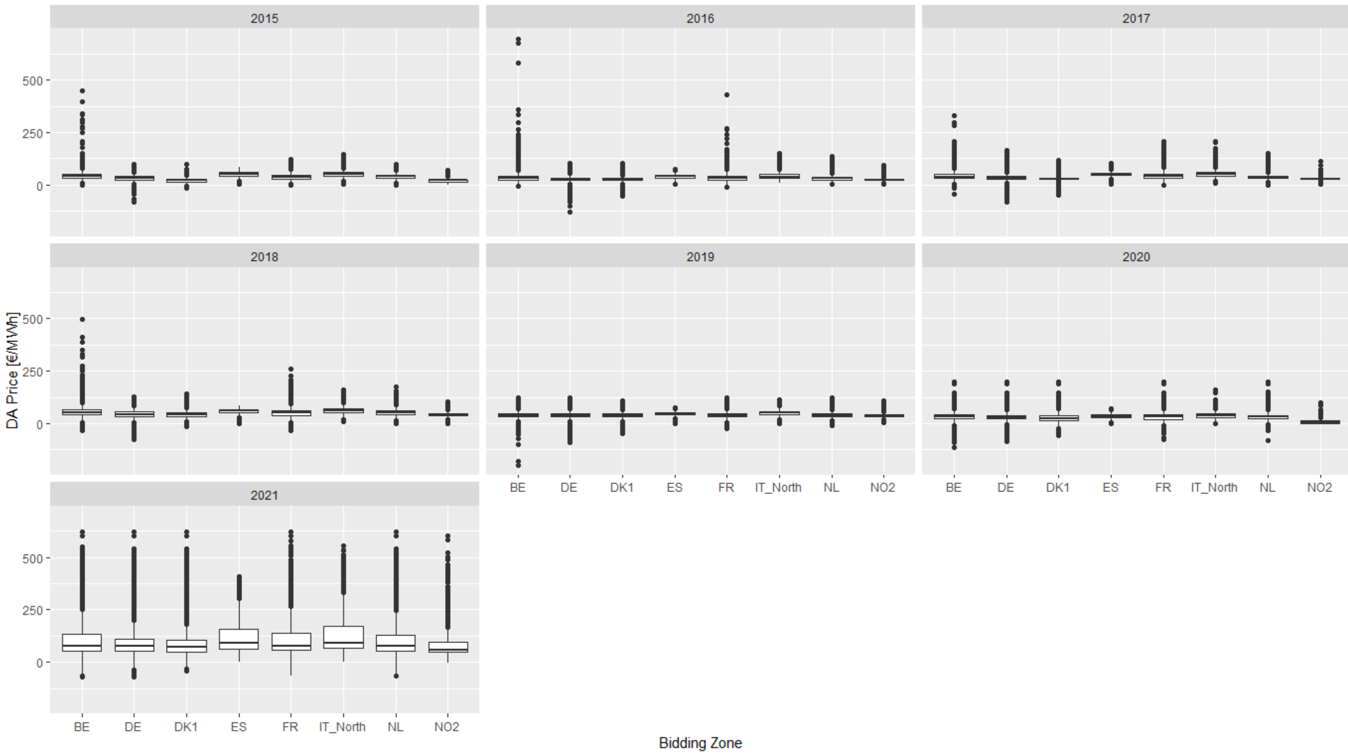

Figure 25: Day-ahead prices boxplots

B Day-ahead price correlation

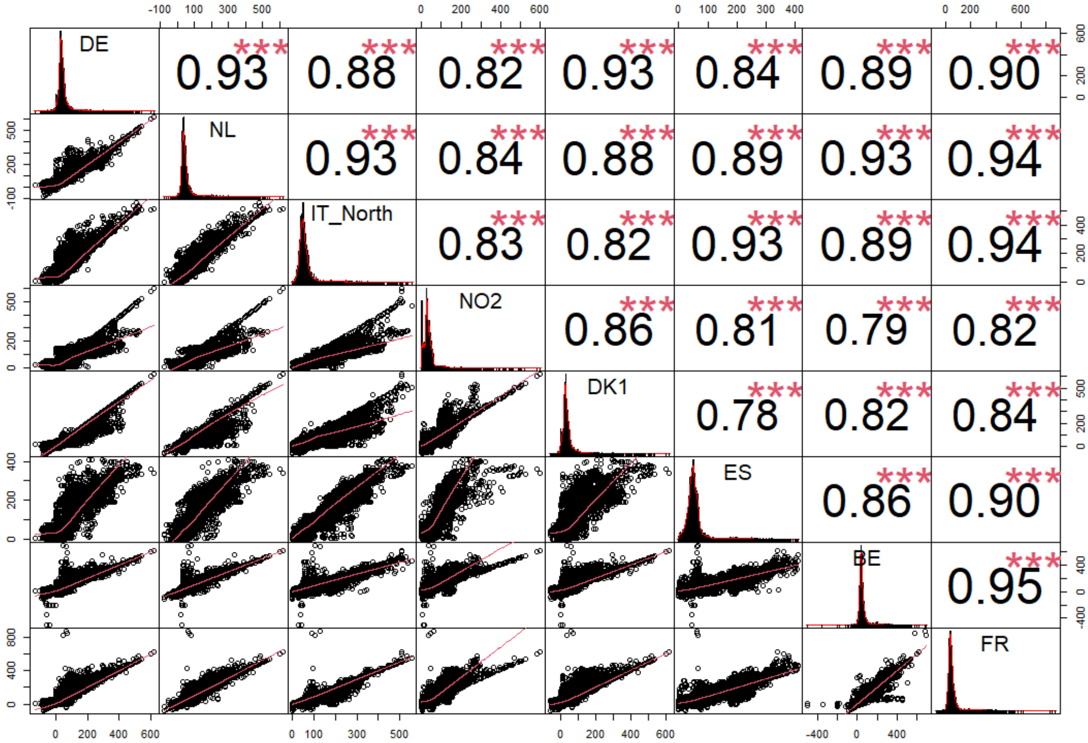

Figure 26: Chart Correlation

C Variability evolution

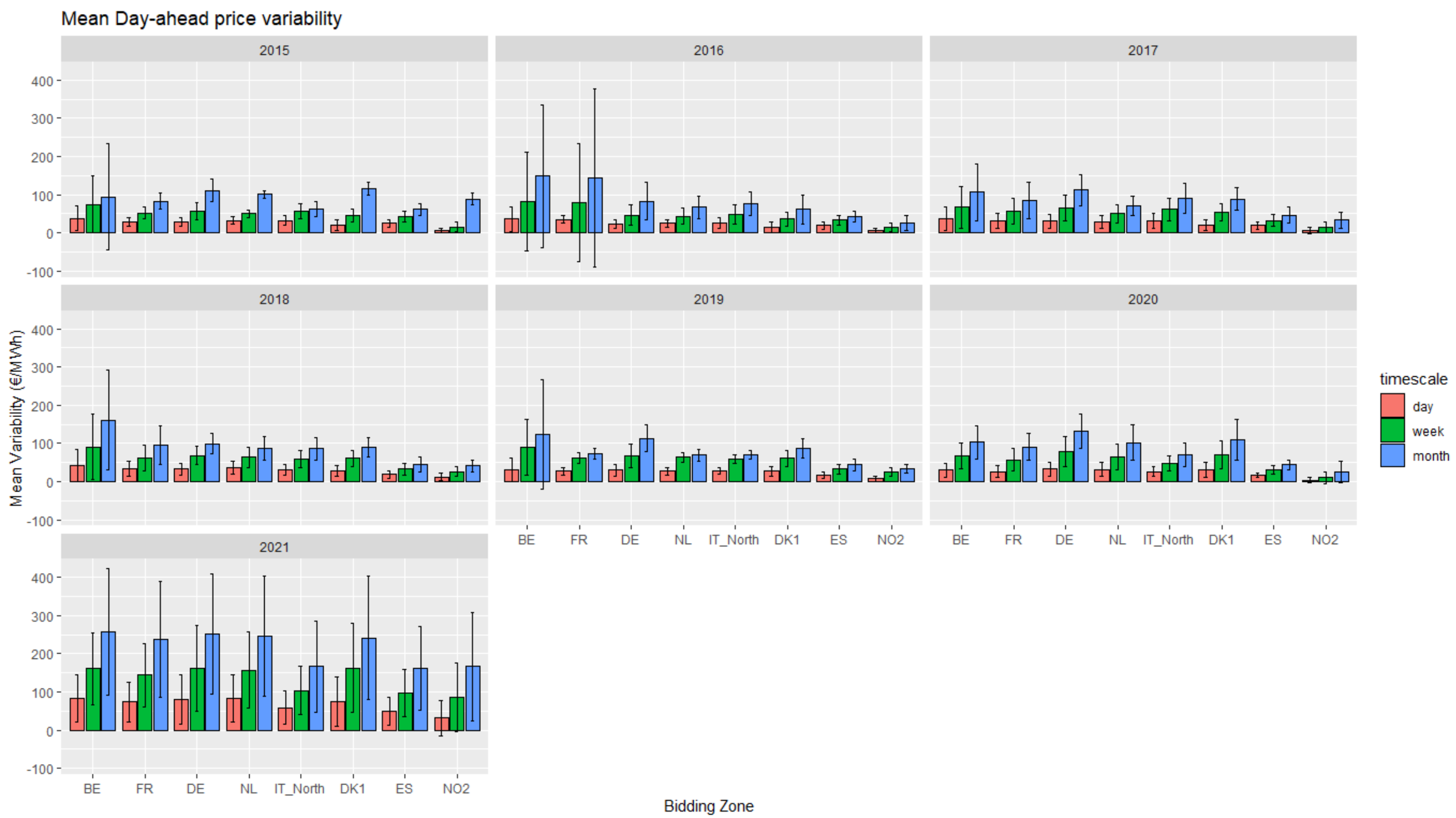

Figure 27: Evolution of the day-ahead variability

D Variability diagrams

In the following diagrams, the variability relationships have been represented. A blue link means that the Student test null hypothesis could not be rejected. A red link means that both Student and Fisher test null hypothesis could not be rejected.

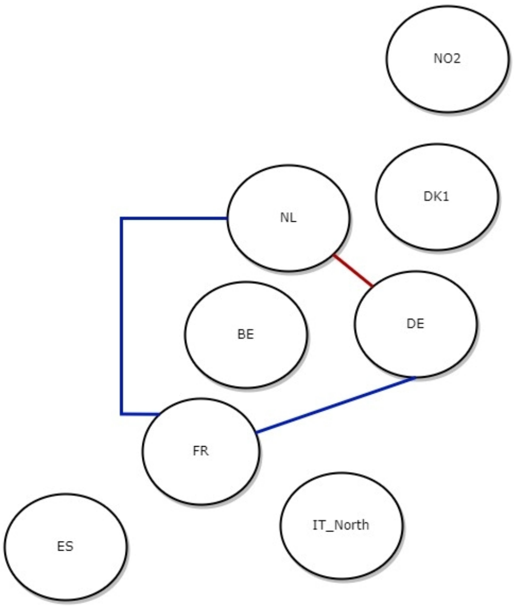

Figure 28: Daily variability diagram

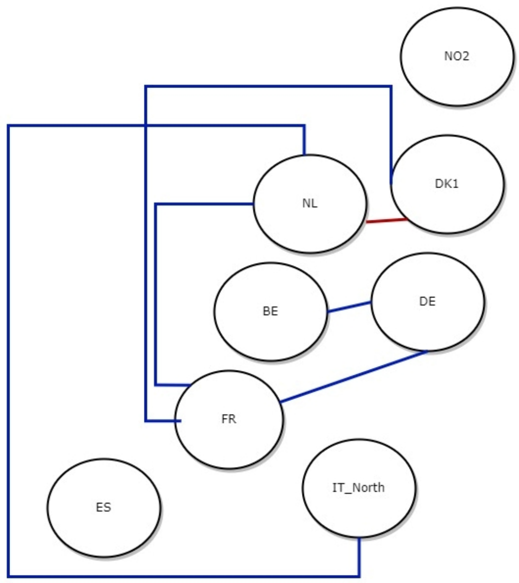

Figure 29: Weekly variability diagram

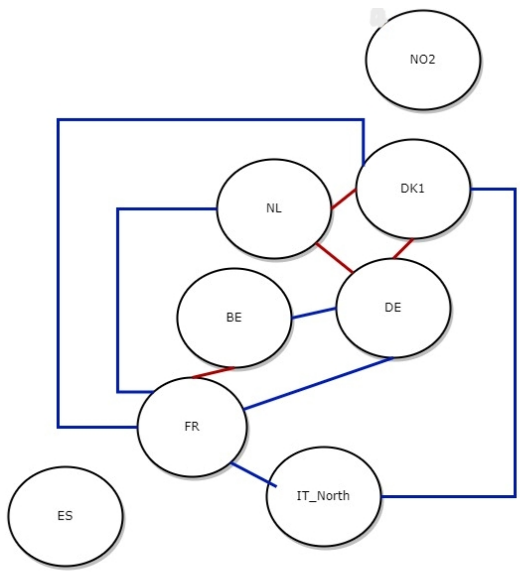

Figure 30: Monthly variability diagram

E Generation Mix

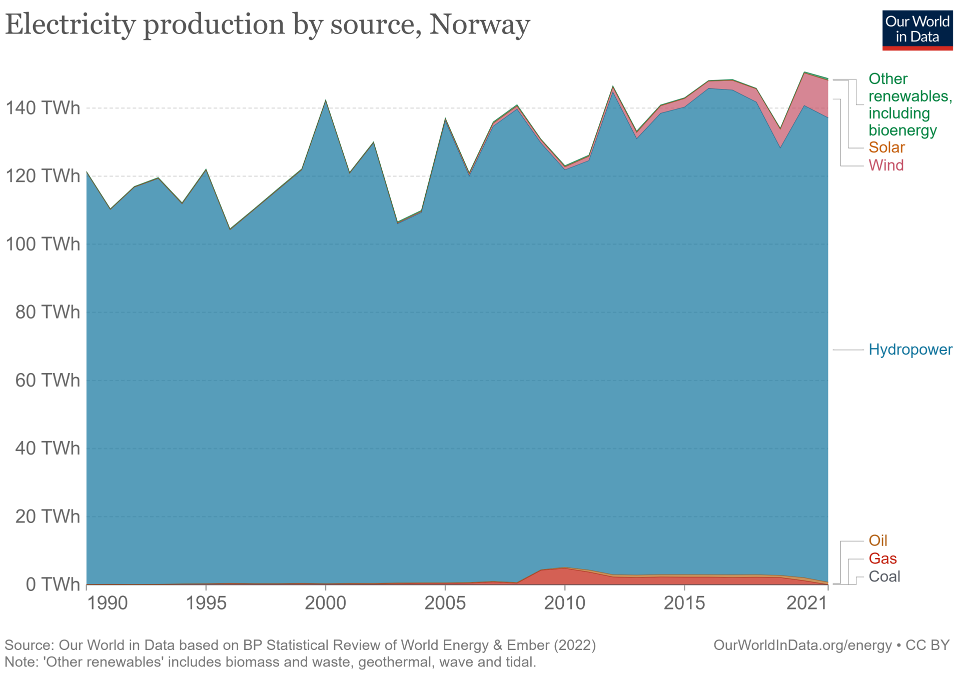

Figure 31: Norway electricity generation mix [58]

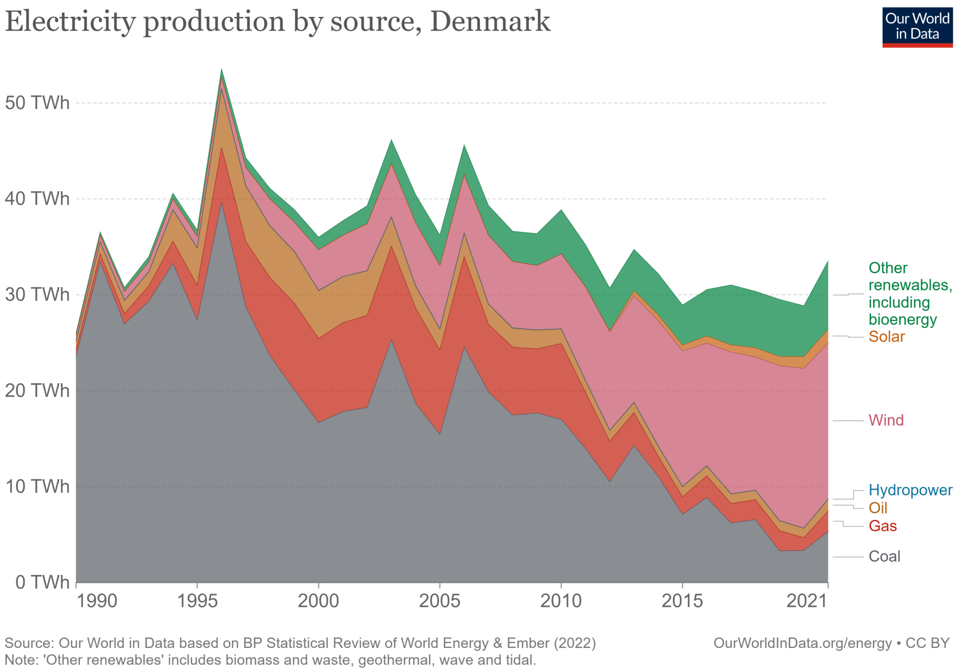

Figure 32: Denmark electricity generation mix [58]

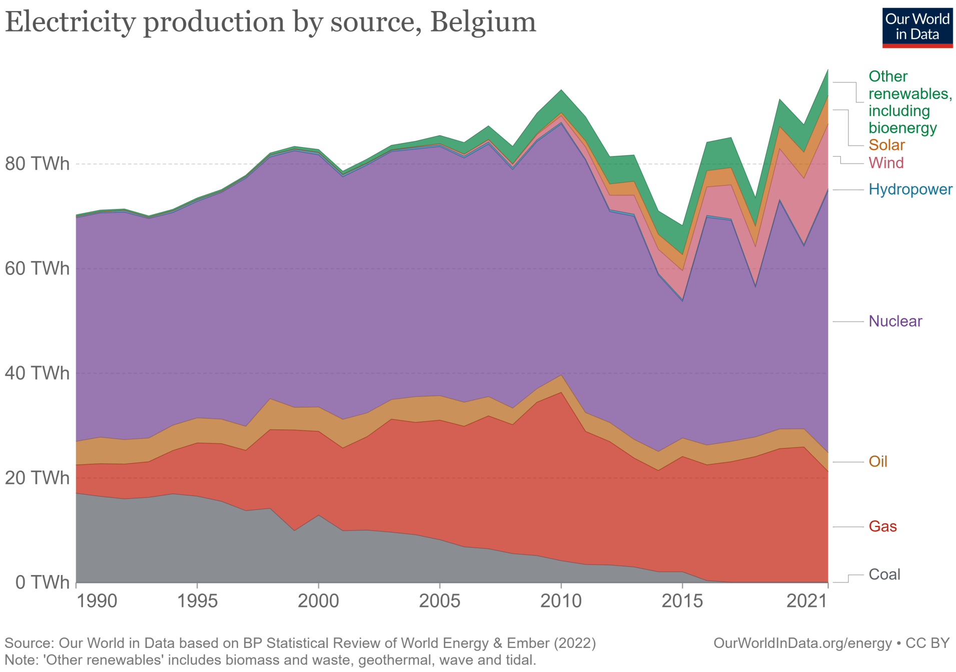

Figure 33: Belgium electricity generation mix [58]

F Day-ahead power prices

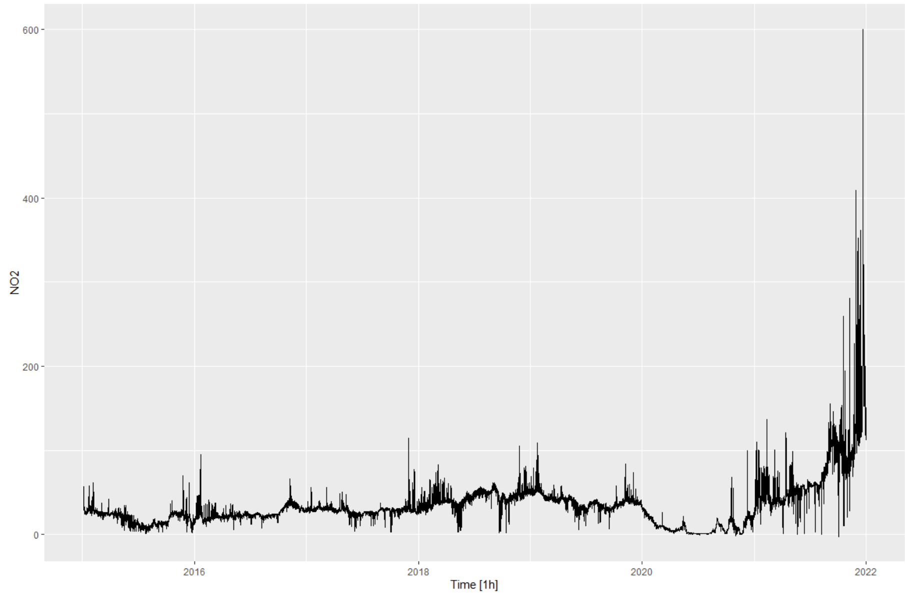

Figure 34: NO2 day-ahead power prices [€/MWh]

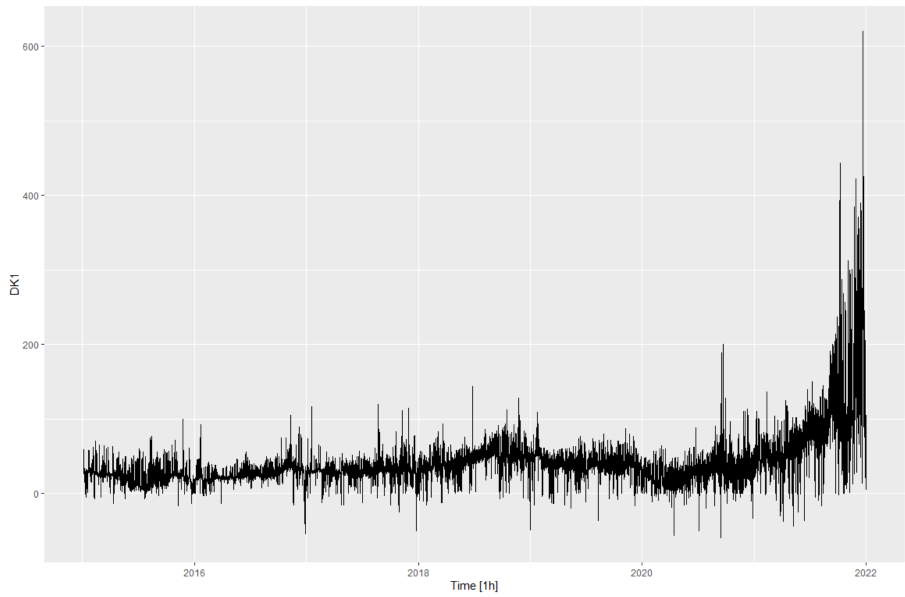

Figure 35: DK1 day-ahead power prices [€/MWh]

G Augmented Dickey-Fuller tests results

```
        Augmented Dickey-Fuller Test

data:  DA_Price_lim_ts$BE
Dickey-Fuller = -16.444, Lag order = 35, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(DA_Price_lim_ts$BE) : p-value smaller than printed p-value
```

Figure 36: ADF test results for Belgium

```
        Augmented Dickey-Fuller Test

data:  DA_Price_ts$NO2
Dickey-Fuller = -7.3596, Lag order = 39, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(DA_Price_ts$NO2) : p-value smaller than printed p-value
```

Figure 37: ADF test results for Southern Norway

```
        Augmented Dickey-Fuller Test

data:  DA_Price_ts$DK1
Dickey-Fuller = -14.184, Lag order = 39, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(DA_Price_ts$DK1) : p-value smaller than printed p-value
```

Figure 38: ADF test results for Western Denmark

H Partial Auto-correlation plots

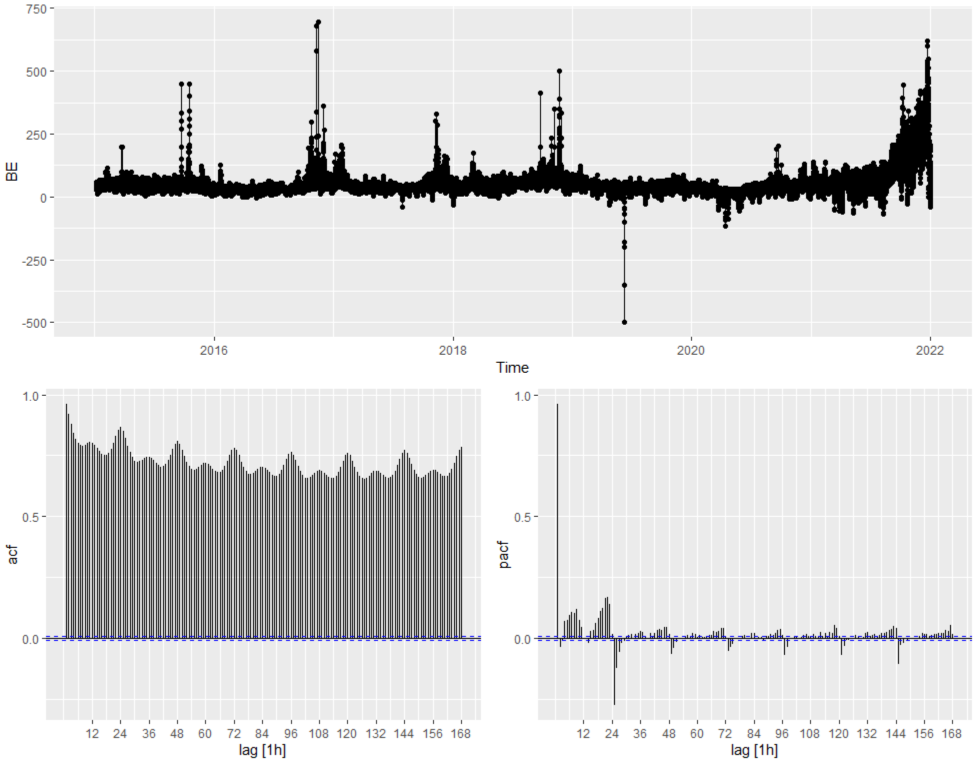

Figure 39: pACF Belgium

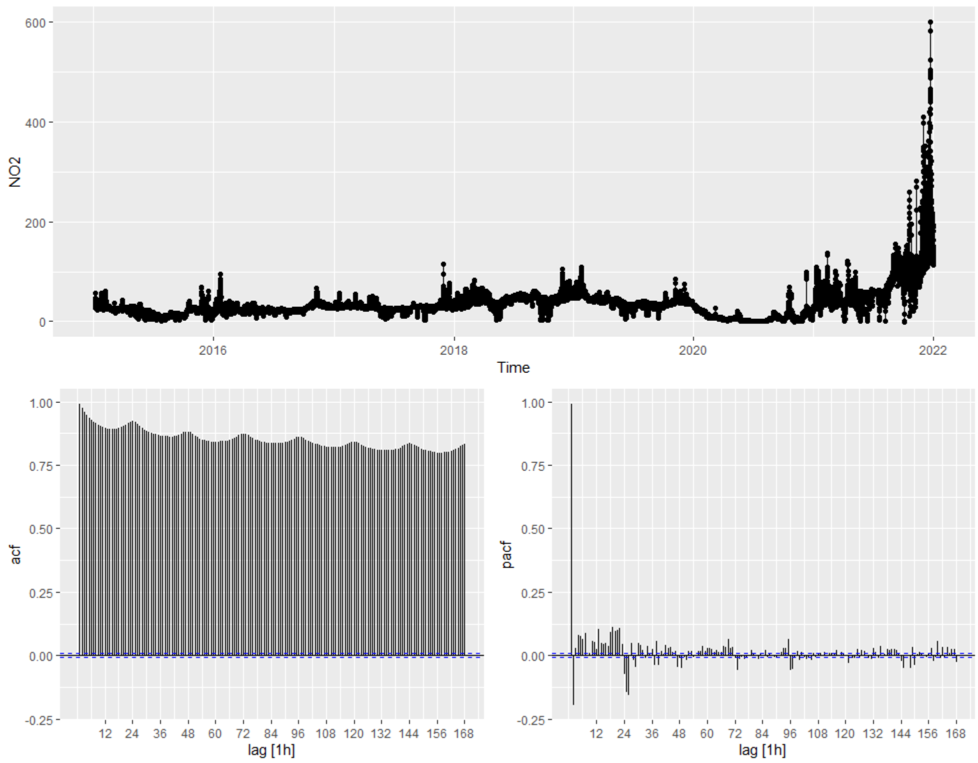

Figure 40: pACF Southern Norway

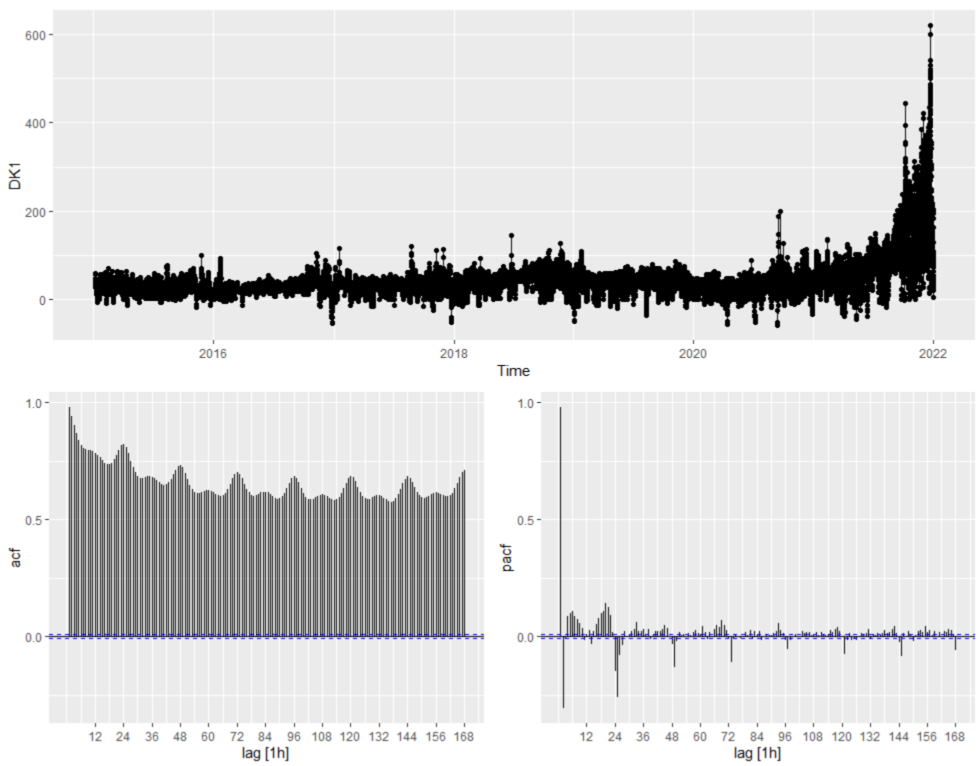

Figure 41: pACF Western Denmark

I Residuals Analysis

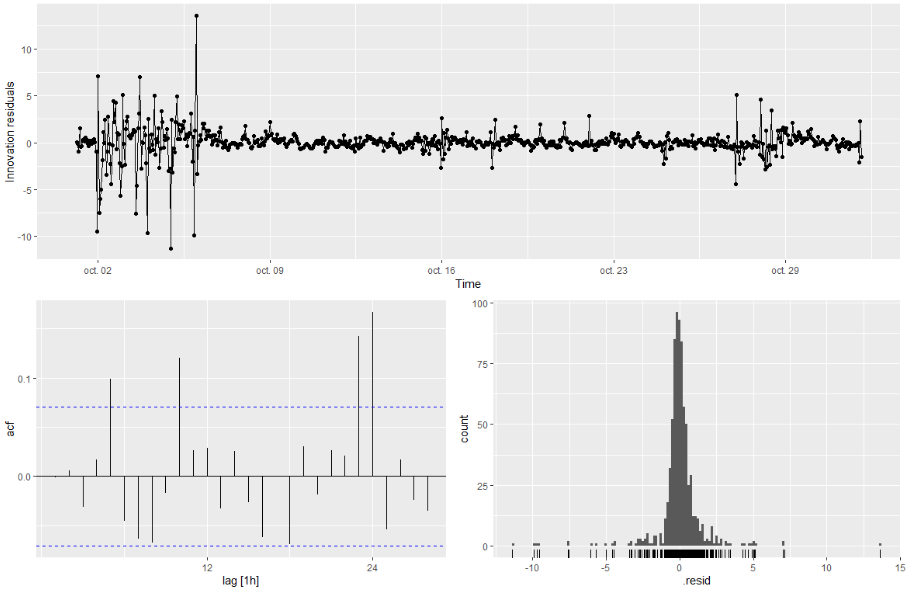

Figure 42: Residuals Southern Norway

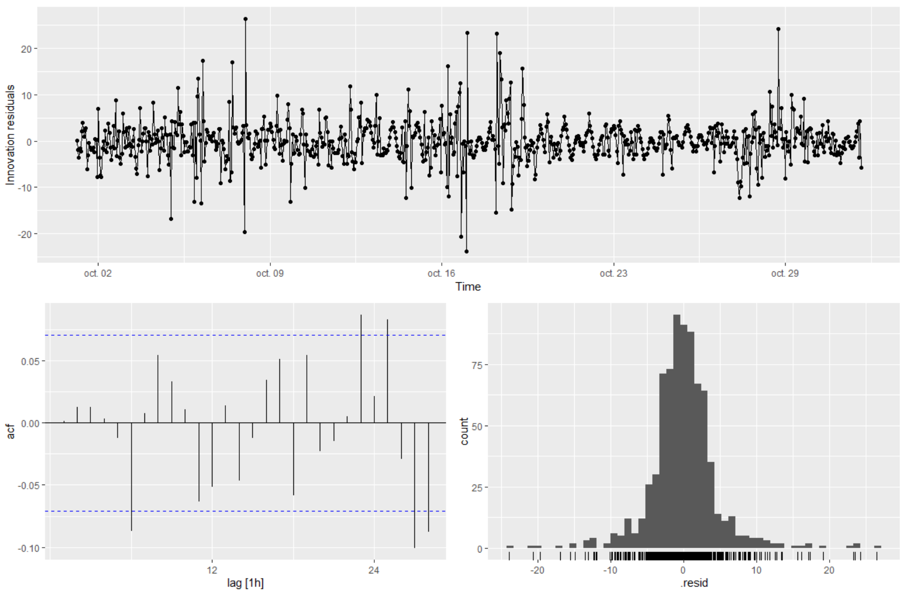

Figure 43: Residuals Western Denmark

J Forecasts versus Actual Prices plots

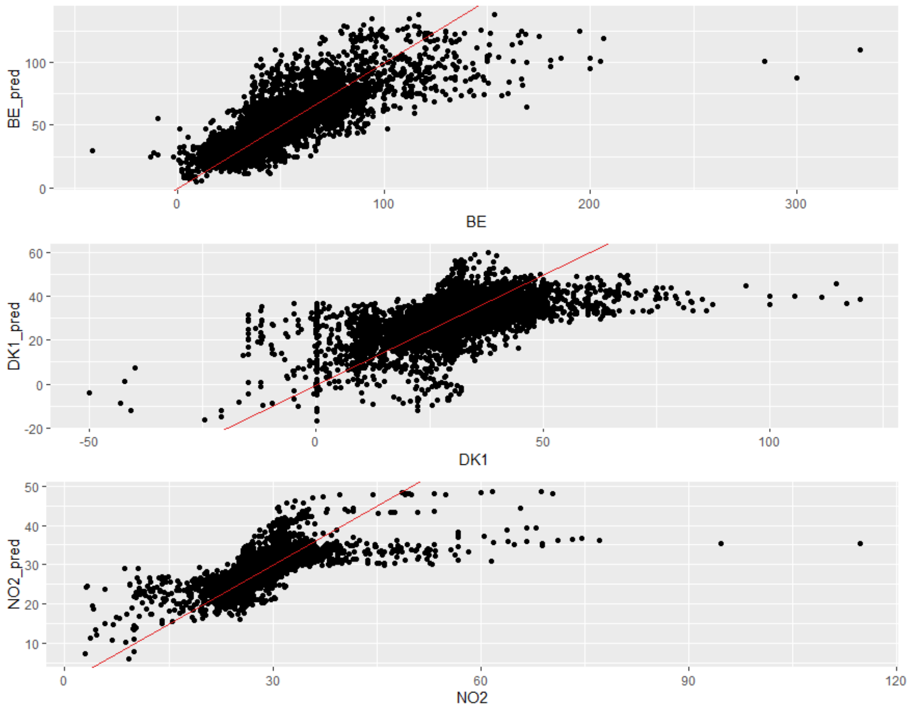

Figure 44: Year 2017

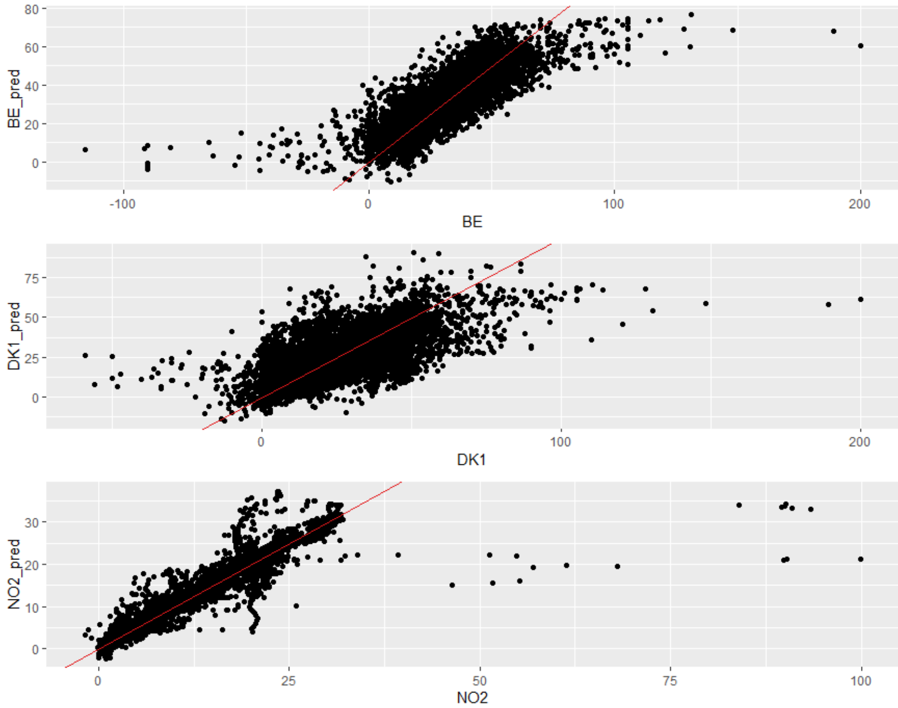

Figure 45: Year 2020

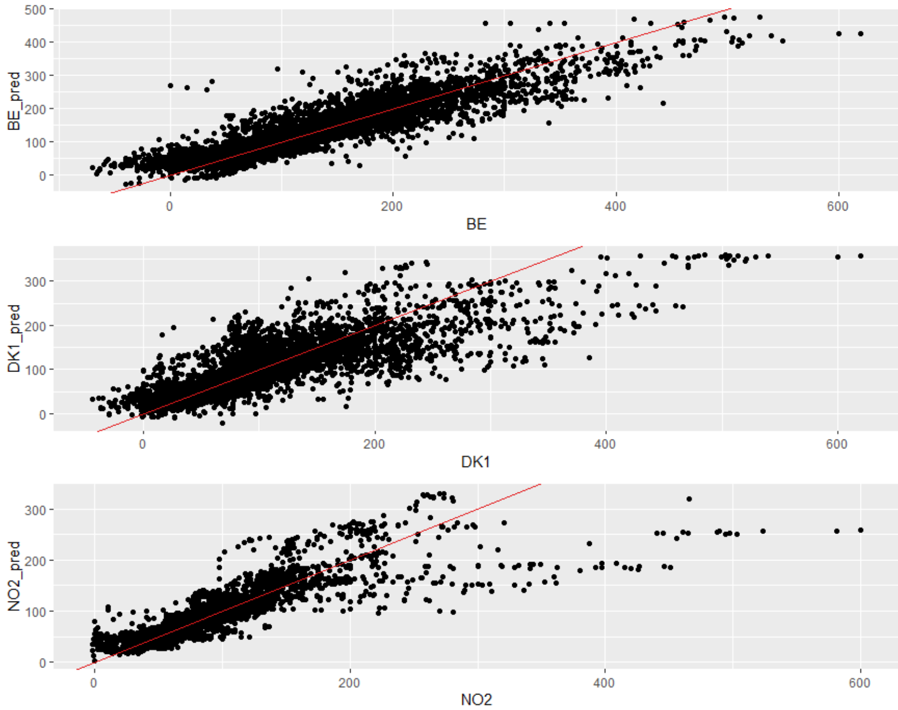

Figure 46: Year 2021

K Sensitivity analysis

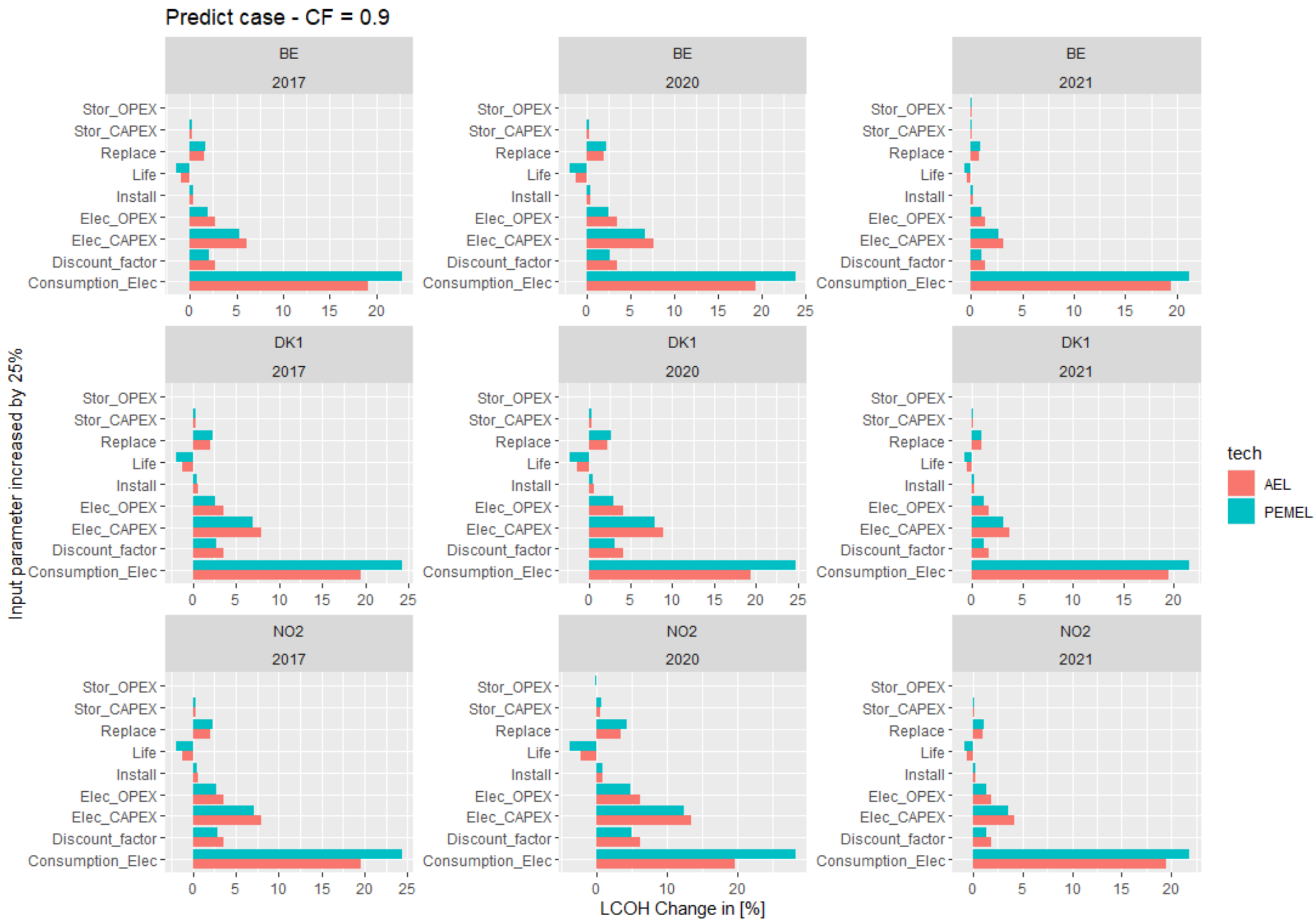

Figure 47: Sensitivity Analysis using Forecasted prices at a Capacity factor of 0.9

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