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Under What Conditions is Production of Hydrogen from Offshore Wind Power Economical?

An Optimisation Approach

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M.Sc in Marine Systems Design
Submission date: June 2021
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Master's Thesis in Marine Systems Design

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Background

In the late 1800s, the automobile was launched without any infrastructure for distribution fuel. Subsequently the costs were high, but in time, diesel and petrol have become the ground rock of our civilisation. Today, green hydrogen faces similar problems, where costs are high as its still relatively new. To contribute to solving this problem, using the inherent volatility of electricity prices and wind speeds to optimise offshore production could be a way forward. Wind farms today are not utilised to their full potential, but by adding a hydrogen production plant to use excess power, the profitability could increase while contributing to cost reduction in green hydrogen. For hydrogen production to be economically viable, it must be priced comparatively to conventional fuels. This thesis seeks to determine how this can be achieved.

Overall aim and focus

The overall objective of this thesis is to investigate under what conditions hydrogen produced from offshore wind power is economically competitive with other more conventional production methods and what the cost-driving factors of a system like this are.

Scope and main activities

The thesis should presumably cover the following main points:

1. An overview of current technology, trends, and forecasts.
2. Modelling of wind speeds and spotprices.
3. Develop an optimisation model to determine optimal configuration of the system. This model is then used to calculate the maximum profit of a system like this.
4. Benchmarking of the model and testing of different scenarios.
5. Investigate the relationship between the input parameters and the profitability of the system by performing sensitivity analyses.
6. Discuss the results of the analyses and give concluding remarks.

Modus operandi

At NTNU, Professor Stein Ove Erikstad will be the responsible advisor.
The work shall follow the guidelines given by NTNU for the MSc thesis.

Stein Ove Erikstad
Professor/Responsible Advisor

"If I had more time, I would have written you a shorter letter."

Blaise Pascal

Summary

This thesis set out to determine under what conditions green hydrogen production from offshore wind is profitable. To answer this question, an optimisation model was built to find the optimal configuration and distribution between electricity export and hydrogen production at low-demand periods for electricity.

As wind speeds and electricity prices are inherently volatile and difficult to predict, Markov chain forecasting using historical data from credible sources was used to simulate time series. These time series were used in tandem with input parameters acquired during the background of this thesis to optimise a power-to-gas system to increase the profitability of wind parks.

During the course of writing this thesis, it has become apparent that hydrogen price and efficiencies of electrolysers play a crucial role in the profitability of a system like this. Using economies of scale and the effects of learning curves, costs and efficiencies are expected to experience great changes over the course of the next decades. This will by all accounts keep reducing production costs of zero-emission hydrogen.

The answer to the research question has two sides to it; yes, it is possible to produce economically competitive hydrogen from offshore wind, but the model is limited to a continuously exporting model, not considering long-term storage to truly take advantage of the volatility of electricity prices.

Sammendrag

Denne avhandlingen hadde som mål å fastlå under hvilke omstendigheter offshore produksjon av grønn hydrogen er lønnsomt. For å gi et svar på dette spørsmålet, ble en optimeringsmodell laget for finne den beste konfigurasjonen og fordelingen av ren elektrisitet eksport og hydrogen produksjon ved lave elektrisitetspriser.

Siden både vindhastigheter og elektrisitetspriser er iboende flyktige og vanskelige å forhåndsbestemme, ble det brukt en Markov chain prediksjonsmodell basert på historisk data for å simulere tidsserier. Tidsseriene ble så brukt i tandem med inputparametere funnet i bakgrunnen av avhandlingen for å optimere et P2G system og øke lønnsomheten.

I løpet av skrivingen av denne avhandlingen, har det blitt mer og mer klart at hydrogenpriser og virkningsgraden til elektrolysører spiller en viktig rolle i lønnsomheten til et slikt system. Ved å bruke stordriftsfordeler og effektene av teknologiske fremskritt er det forventet at både virkningsgrad og kostnader vil oppleve store forandringer i tiårene som kommer. Dette vil etter alt å dømme, fortsette å redusere kostnadene til nullutslipps hydrogen.

Svaret på forskningsspørsmålet har to sider ved seg; ja, det er mulig å produsere økonomisk bærekraftig hydrogen fra offshore vindkraft, men modellen er begrenset ved at den ikke kan lagre hydrogen strategisk for langsiktig re-elektrifisering for å utnytte flyktigheten i strømpriser.

Preface

This thesis is part of my Master's degree in Marine Technology with specialisation in Marine Systems Design at the Department of Marine Technology from the Norwegian University of Science and Technology. The thesis corresponds to 30 ECTS and was written during the spring semester of 2021.

The thesis' contents are the engineering and economics of offshore wind energy, hydrogen production and regeneration. During the writing of the thesis, I have expanded my theoretical background, learned new software and concepts, and it has in its whole been a rewarding semester. Although testing, I believe the thesis has provided me with valuable experience in the energy market, different fuel cell and electrolyser technology and programming.

As last year, the COVID-19 pandemic has affected the working habits of both students and professors. The meetings with my supervisor have been a mix of physical and virtual, depending on the current situation. Although it has taken its toll on my motivation, I feel we have handled it well. I would like to thank my supervisor, Professor Stein Ove Erikstad, for challenging me while still being supportive and giving valuable guidance throughout the process of this thesis.

Last but not least, I would like to extend a special thank you to my colleagues and friends at the office, Vincent, Andreas, Ingvild, Dani and Malin. I wish you all the best in the years to come.

Trondheim

June 10, 2021

Benjamin Madsen

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Nomenclature

CAPEX	Capital expenditure
OPEX	Operational expenditure
P2G	Power-to-gas
PEMEC	Polymer electrolyte membrane electrolysis cell
AEC	Alkaline electrolysis cell
SOEC	Solid oxide electrolysis cell
FCEV	Fuel cell electric vehicle
PAFC	Phosphoric acid fuel cell
AFC	Alkaline fuel cell
PEMFC	Polymer electrolyte membrane fuel cell
SOFC	Solid oxide fuel cell
Δ_f°	Gibbs free energy
HHV	Higher heating value
LHV	Lower heating value
v_c	Cut-in wind speed
v_r	Rated wind speed
v_f	Cut-off wind speed

Chapter 1

Introduction

According to the U.S. Energy Information Administration, the world's energy consumption is steadily increasing and will increase with nearly 50% from 2010 values by 2050 [EIA15]. Knowing that the global consumption shows no sign of abating, and the fact that global surface temperature is expected to increase somewhere between 1.6 and 5.5 degrees centigrade by 2100 with the current trend, production of green hydrogen is considered paramount to provide enough energy while still being more environmentally friendly than fuels like coal, natural gas and oil [IPC01].

The hydrogen economy is an ambitious goal of using almost exclusively hydrogen as the world's commercial fuel, much like oil and gas is used today. If the hydrogen economy is to be a realistic scenario, the production of hydrogen would have to be both economically and environmentally competitive compared to other more conventional energy carriers. Technological advancements in fuel cell and electrolyser technology must also occur to be able to gain market shares from power plants and transportation vessels/vehicles. If this is to happen, the entire world would prosper from a lower dependency of hydrocarbons and an increased environmental quality. Notwithstanding, for the hydrogen economy to become reality, several technical, political and social challenges must be handled. Despite being the most abundant element in the universe, hydrogen does not occur naturally in its pure form. Consequently, it must be synthesized and must be recognized as an energy carrier rather than an energy source.

As the infrastructure for low-emission hydrogen production and distribution is at an early stage, the cost of producing and distributing the fuel is very high. When the infrastructure is insufficient and costs are high, few are willing to bet on hydrogen, and companies have little incentive to invest to try and solve this problem. However, without investing in green hydrogen technology, the prices will not decrease enough for large scale distribution and consumption. This chicken-and-egg dilemma has existed ever since research and development of clean hydrogen began. This can be compared to the early 20^{th} century when automobiles were developed without any infrastructure for distribution of gasoline, with the only place you could buy gasoline was the pharmacy. Knowing that we as a society have overcome similar challenges before, leads to believe that a hydrogen society can be achieved.

Considering that both the electricity market and wind speeds are inherently volatile and difficult to predetermine, the idea of creating a power-to-gas hybrid system to make use of excess power from wind has gotten attention lately. Hydrogen produced through water electrolysis by electricity supplied from wind power could potentially increase the revenue and profit of wind farms while reducing our impact on the environment. Hydrogen could be produced while electricity prices are low, both based on the season, but also during low demand periods during the day. The objective of this thesis is to investigate under what conditions a system like this can be used to optimally produce clean hydrogen for export in low electricity demand periods and re-generation in times of high electricity demand.

The main topics up for discussion are, among others, what fuel cell and electrolysis technologies are the most applicable for a system like this. Comparable green hydrogen projects will be investigated to see how others are approaching the same task. The electricity-, wind power- and hydrogen market will be analysed to determine if a system like this can be more profitable in the future. The methodology of this thesis will discuss system configuration, prediction models and an optimisation model. The optimisation model will be benchmarked by forcing the model to only export electricity. Using the benchmark, several cases with varying input parameters will be compared to the benchmark. A sensitivity analysis will be carried out to determine what parameters affect the profitability of a system like this the most. Finally, the results will be discussed and proposals for other uses or improvements of the model will be made.

Chapter 2

Background

The background chapter will give a rationale for this thesis. Some topics are covered to a larger extent than others, but seek to provide the reader with the most important information. The primary objective of this chapter is to provide the author and reader with the basic workings of wind-powered hydrogen production and how it might change in the future.

Section 2.1 covers hydrogen properties and green hydrogen projects in either planning, development or operation. Section 2.2 covers electrolysis with relevant cost-driving factors. Section 2.3 discusses hydrogen storage and compression. Section 2.4 covers the basic functioning, costs and efficiencies of various fuel cell technologies. Section 2.5 explains how the electricity market has developed through the years and how it is distributed among renewables and non-renewables. Section 2.6 covers the cost of wind power, price movement and distribution among onshore and offshore wind power. Section 2.7 explains how the hydrogen market is built up, costs of production today, the global hydrogen demand and projected production costs.

2.1 Hydrogen

Hydrogen is a colour-, odour- and tasteless, flammable gaseous element. It is the simplest of all chemical elements with a single electron orbiting a nucleus comprising a single proton. Hydrogen exists in its purest form as a pair of hydrogen atoms, H_2. The first known property of hydrogen is that, if reacted with oxygen, it forms H_2O, subsequently owning the name of hydrogen, which is derived from Greek words meaning "maker of water".

Being the most abundant element in the universe, one would assume pure hydrogen would be in significant supply, but this is not the case. Hydrogen occurs in tiny amounts in its natural pure form, making up only 0.14 % of the Earth's crust by mass [Jol20]. On the other hand, hydrogen occurs in large quantities combined with oxygen in oceans, rivers, the atmosphere etc., and is a vital part of natural gas. Hydrogen can be separated from natural gas and water using natural gas reforming and electrolysis, respectively.

2.1.1 Hydrogen Properties

	Unit	Hydrogen	Methane
Molecular weight	g/mol	2.016	16.043
Specific volume	kg/m^3	0.08376*	0.65*
Liquid density	kg/m^3	70.8**	422.8**
Boiling point	Kelvin	20.4	111.15
Autoignition temperature	Celsius	585	537
Flammable range	%	4-74***	4-16.4***
Ignition energy	mJ	0.02	0.28
Lower heating value	MJ/kg	120	50
Higher heating value	MJ/kg	142	55

Figure 2.1: Properties of hydrogen compared with methane [Des01]

Table 2.1 shows some of the key properties of hydrogen with a comparison column containing the same parameters for methane. Some parameters are more important than others when investigating hydrogen production, which is why the table is as limited as it is.

$^{*}:\ Standard\ temperature\ and\ pressure\ (293.15\ K,\ 1\ atm)$

$^{**}:\ Values\ given\ for\ liquid\ phase\ (respective\ boiling\ point,\ 1\ atm)$

$^{***}:\ Values\ given\ for\ 293.15\ K,\ 1\ atm$

The largest problem with hydrogen as a fuel carrier is its density. At standard temperature and pressure, the density is only 0.08376 kg/m^3, while cryogenically stored it is still only 70.8 kg/m^3, which is about 16.7% that of methane. From a logistical standpoint, the low specific volume, liquid density and boiling point of hydrogen poses some of the largest challenges. Cryogenic storage brings costly processes, but hydrogen at standard temperature and pressure results in a low specific volume. Depending on the use, cryogenic storage might be worth the extra cost, while others might use relatively little pressurisation to satisfy the need.

The flammable range of hydrogen also poses problems as the range is very large compared to other energy carriers. The ignition energy is, on the other hand, only 1/14 that of methane. The autoignition temperature of hydrogen should not affect a low-temperature system, e.g. polymer membrane, in any significant way, but could pose problems to other systems, e.g. molten carbonate or solid oxide systems.

2.1.2 Green Hydrogen Projects

There are multiple green hydrogen projects currently either in planning, under construction or in operation. Most projects used to be in the MW-scale, but in recent years, several large projects in the GW-scale are under construction. Some of these large-scale projects will be discussed in this section of the thesis.

The HyDeal Ambition is a solar-powered electrolyser system distributed over several locations across Western Europe. The planned system consists of 95 GW of solar power, running 67 GW of electrolysers in Spain, France and Germany. The project is funded by 30 major energy players. HyDeal Ambition is expected to export 3.6 million tonnes of green hydrogen across Europe at a rate of €1.50/kg by 2030. The project is at an early stage of development and is yet to have a public expected cost [EA21].

The Asian Renewable Energy Hub is a system combining onshore wind power and onshore solar power to run 14 GW of electrolysers. It is located in Pilbara, Western Australia, and the completed system is expected in 2027-2028. The system is expected to produce 1.75 million tonnes of hydrogen per year, which translated to just short of 10 million tonnes of green ammonia, which will be the export of the project. Since ammonia is the product of the system, there are no known prices for the produced hydrogen, but the expected cost of the project is $36 billion [Ltd20].

NortH2 is located in Eemshaven, Netherlands, and is powered by offshore wind power. The system's goal is to power heavy industries in Germany and the Netherlands, and is a cooperative project between Shell, Equinor, RWE, Gausine and Groningen Seaports. The expected output of the system is one million tonnes of hydrogen per year, with capacity increasing from 1 GW in 2027 to 4 GW by 2030 [Equ20].

AquaVentus is an offshore wind-powered system project due in 2035 located in Heligoland, Germany. The planned use of the hydrogen is general sale in the European hydrogen network. It will have a capacity of 5 GW by 2030 and 10 GW by 2035, which will result in around one million tonnes of hydrogen export per year. The project is at an early stage and is planned to be constructed in stages. There are yet to come any concrete costs related to the project as it was announced in August 2020 [RWE21].

HyEnergy Zero Carbon Hydrogen is located in the Gascoyne region, Western Australia. It is, as the Asian Renewable Energy Hub, a combination of wind and solar. The planned use of the hydrogen is both for green hydrogen export as well as ammonia for use in heavy transport and industry. If successful, hydrogen from the system will also be implemented into a local natural gas pipeline for export to Asian markets. The project is due in 2030, but there are no expected production volumes as of now [ups21].

Project	Location	Power source	Capacity [GW]	H_2 output [mill t/yr]	Completion Date
HyDeal Ambition	Europe	Solar	67	3.6	2030
Asian Renewable Energy Hub	Australia	Wind/solar	14	1.75	2027-2028
NortH2	Netherlands	Wind	4	1	2030
AquaVentus	Germany	Wind	10	1	2035
HyEnergy Zero Carbon Hydrogen	Australia	Wind/solar	8	N/A	2030

Table 2.1: Comparison of hydrogen projects

2.2 Electrolysis

Electrolysis uses electricity to split H_2O into hydrogen and oxygen using an electrolyser. Electrolysers work a lot like a fuel cell, with a cathode and an anode separated by an electrolyte. There are slight variations in the way electrolysers work, mostly because of the use of different electrolytes. In polymer electrolyte membrane electrolysers, water reacts at the anode. This forms oxygen and positively charged hydrogen ions, H^+ and is shown in Equation 2.1 below [Ene].

$$2H_2O \rightarrow O_2 + 4H^+ + 4e^- \tag{2.1}$$

The electrons move through an external circuit while hydrogen moves through the membrane to the cathode. Hydrogen ions then combine with electrons at the cathode to produce hydrogen gas. This is shown in Equation 2.2 below.

$$4H^+ + 4e^- \rightarrow 2H_2 \tag{2.2}$$

Since electrolysis uses electricity rather than heat and carbon-rich fuels to produce hydrogen, this method can easily result in zero-emission hydrogen production. It is though, dependent on electricity from renewable or zero-emission sources like wind and nuclear energy to be a valid alternative to fossil fuels. In some countries, like Norway, Denmark and the Netherlands, electrolysis could be a suitable alternative to other production methods because of their extensive use of wind- and hydro-power. Producing hydrogen during low-demand periods for electricity can utilise the otherwise wasted energy that the wind possesses. Although electrolysis may not be the best alternative for all nations, it may be a suitable alternative to other production methods for countries that already possess environmentally friendly and economically viable methods for electricity production.

2.2.1 Electrolysis Costs and its Constituents

The cost of hydrogen production is dependent on capital costs of electrolysers, the degree of utilisation, cost of labour and the average cost of electricity during production. A high utilisation degree decreases the influence of capital expenditure, but also increases the average electricity cost as more hours of high-cost electricity are included in the production phase. According to the *Compendium of Hydrogen Energy 2016* [BBV16], the optimal hours of operation for a grid-connected electrolyser are in the range of 3000-6000 hours per year, yielding a utilisation degree of 34.25-68.50%. This will of course depend on the location of production as different regions have different electricity demands. For a P2G system, the optimal operating hours may vary significantly as it is not only dependent on electricity prices anymore, but the distribution of wind speeds as well.

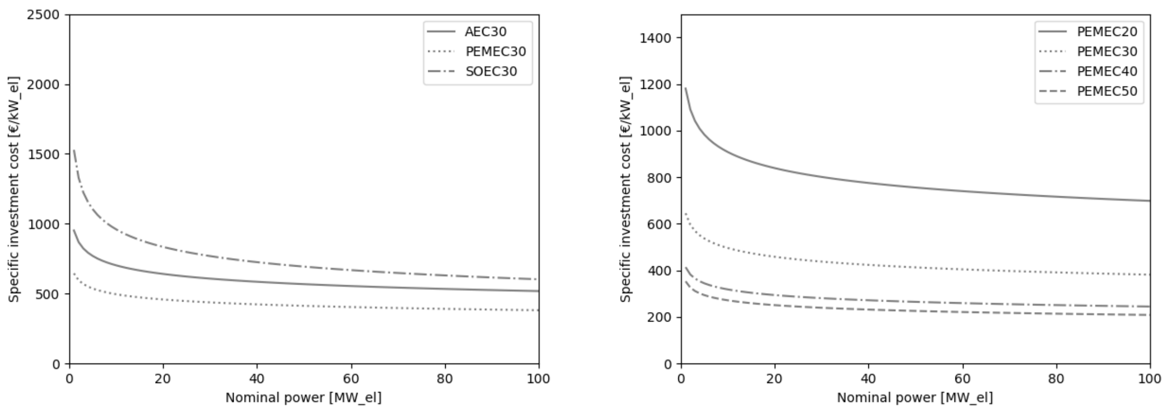
2.2.1.1 Capital Investments

There are several methods of electrolysis, among others: polymer electrolyte membrane (PEMEC), alkaline (AEC) and solid oxide (SOEC). To make a solid decision on what technology to use, one should consider how both learning curves and economies of scale will affect the capacity cost in the future. According to Store & Go [Goa], the capital cost of electrolyser systems will decrease significantly during the next 30 years.

Technology	Cost [1000 NOK/MW]			Learning rates [%]		
	2017	2030	2050	2017	2030	2050
PEMEC	12 000	5 300	2 900	16.8	13.8	12.0
AEC	11 000	7 600	4 400	13.1	12.3	11.0
SOEC	25 000	10 900	6 100	15.6	12.4	11.2

Table 2.2: Potential cost reduction for a 5 MW_{el} system [Gob]

The effects of learning curves are shown in Table 2.2. From this table, AEC is the most affordable technology today, but during a relatively short time span, PEMEC will surpass AEC. SOEC is the most costly option today, but is also expected to be subject to a drastic cost reduction by 2050. PEMEC and SOEC are expected to have a cost reduction of approximately 75% by 2050, while AEC will experience a 60% reduction. With this in mind, PEMEC may be the better choice for the near future, but this might change in time as SOEC becomes a more mature technology.



(a) Comparison of economies of scale, 2030

(b) Polymer electrolyte membrane electrolysis

Figure 2.2: Showing effect of learning curve and economies of scale [Gob]

As shown in Figure 2.2a, PEMEC is expected to be the most affordable option in 2030, sharing a relatively similar curve shape to AEC, but with a lower starting point. The effect of economies of scale is more severe on SOEC, but PEMEC remains the more affordable technology. A more in-depth graph of PEMEC is shown in Figure 2.2b, showing how both economies of scale and learning curves, affects the cost.

2.2.1.2 Operational Expenses

The operational costs of electrolysis include all costs of operating the electrolysis process, but in this thesis, electricity consumption is handled separately. This is because this is the most fluctuating cost and the most important parameter in offshore wind power production. Usually, electricity is the largest expense in green hydrogen production over its lifetime. This means that the efficiency of the electrolyser is very important as it can cause sizeable differences in costs over the lifetime of an electrolyser system. The last major expense is maintenance costs. Maintenance costs vary from electrolyser to electrolyser, but they are often assumed to be between 1-3% [Chr20].

It is also worth mentioning that for electrolyser systems running on an exceedingly high utilisation degree, the reliability of the entire system is especially important as downtime can amount to significant costs, especially offshore. Since electricity cost often is the largest fraction of the total operational expenses, hydrogen production while the price of electricity is below a certain value is paramount for the system to be economically viable. To assess this problem, spotprices can be analysed.

Figure 2.3 on the next page shows how electricity prices vary through an *average day* for each month. To elaborate, each month's data is represented by 24 data points instead of around 30. This is done to clearly distinguish at what points of an average day electricity prices are at their lowest. Each average day is made up of 24 data points, each one being the average spotprice for hour n for all days in the given month for all years. The mathematical formulation of how this is calculated is shown in Equation 2.3. This creates a time series comprising 288 data points with clear indications of how the spotprices vary throughout the day depending on the month. spotpriceVisualisationRaw.py in Appendix A.4 provides a more in-depth explanation of this calculation if needed. The data from the figure below is derived from NordPool's spotprices for Oslo between 2013 and 2020 [Nor20].

$$\left[\begin{array}{c} January \quad 01:00:00 = mean\begin{bmatrix} 01/01/2013 & 01:00:00 \\ 02/01/2013 & 01:00:00 \\ & \vdots \\ 31/01/2020 & 01:00:00 \end{bmatrix} \\ \\ January \quad 02:00:00 = mean\begin{bmatrix} 01/01/2013 & 02:00:00 \\ 02/01/2013 & 02:00:00 \\ & \vdots \\ 31/01/2020 & 02:00:00 \end{bmatrix} \\ \vdots \\ December \quad 24:00:00 = mean\begin{bmatrix} 01/12/2013 & 24:00:00 \\ 02/12/2013 & 24:00:00 \\ & \vdots \\ 31/12/2020 & 24:00:00 \end{bmatrix} \end{array}\right] \tag{2.3}$$

Since CAPEX and OPEX are relatively stable, electricity costs will be the most important factor to investigate. The data from Figure 2.3 can be used to evaluate at what time of day and at what time of year it is economically viable to produce hydrogen offshore.

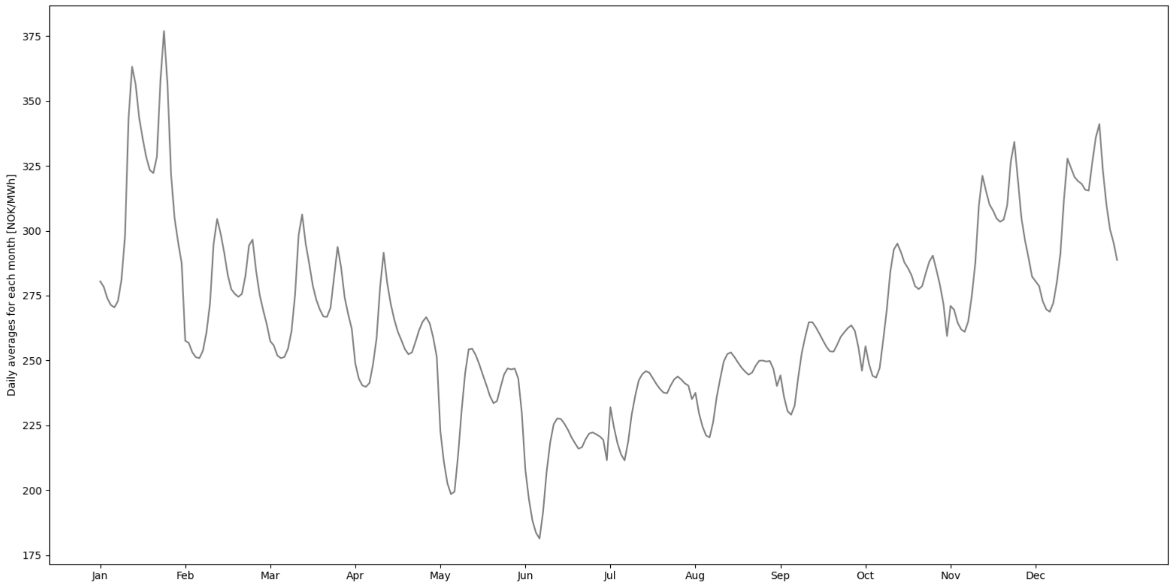


Figure 2.3: Shows an *average day* of each month's spotprices

In addition to electricity prices, the cost of water can also add up to significant sums. Water usage of electrolysers varies between 9-10 liters per kg of hydrogen with a nominal usage of 10

L/kg. This is about 0.27-0.33 L/kWh of hydrogen power. The cost of water used in electrolysis is between $1.02-6.82 per kL, with a nominal cost of $ 1.44/kL. This translates to about NOK 15 per kL [Yat+20]. The nominal values will be used later during the optimisation.

2.2.1.3 Efficiency of electrolysis

Efficiency is one of the most important factors when choosing electrolysers for a P2G system. This is because approximately 2/3 of the operating costs are related to energy and how it is utilised. Electrolysers are most efficient when running on lower loads due to lower current density. For simplicity, the efficiency of the electrolysers will be assumed constant, independent of load in this thesis. AECs are usually the most efficient as of today, but PEMECs are expected to be competitive soon as AEC is a more mature technology [B K02]. PEMECs typically operate at 77-80% efficiency [Pow17] [RWE18], but have a theoretical potential of about 94% according to Bellona [B K02]. AECs are best suited for hydrogen production when it is connected to the grid, while PEMECs are best suited for production when the output is varying. This makes PEMECs well suited for offshore production as both the wind and electricity markets are volatile and difficult to predict.

2.2.1.4 Summary of electrolysis

After consideration, PEMEC became the choice of electrolysis technology for this thesis. This is due to its high efficiency, short start-up time and low cost, both today and predicted costs. Table 2.3 summarises the most important information for PEMECs. Another noteworthy fact about PEMECs is that the output pressure is relatively high compared to other electrolysis cells at 3 MPa. This is expected to increase to 6 MPa according to a study by Tractebel and Hinicio [TH17].

Table 2.3: Summary of PEMEC

	PEMEC			
Efficiency [%]	Low	Med	Max	
	60	80	94	
Capacity cost	2020	2030	2040	2050
[1000 NOK/MW$_{el}$]	7 000 - 11 800	3 800 - 6 500	2 450 - 4 150	2 100 - 3 500

2.3 Compression and storage

When storing hydrogen, there are several factors to consider. Compression costs increase while storage volume decrease with increased pressure, so the objective is to find the perfect balance between compression costs and storage volume. In this thesis, this will be analysed qualitatively as an in-depth analysis of compression/storage costs is considered outside the scope. Table 2.4 shows the capital expenditure of storage and compression [IEA15].

Table 2.4: Compression and storage costs of hydrogen

	Efficiency [%]	CAPEX [NOK/MWh$_{H_2}$]	Life time [years]
Pressurised storage	≈ 100	49 900 - 83 150	20
Liquid storage	0.3% boil off/day	6 650 - 83 150	20
		CAPEX [NOK/MW$_{H_2}$]	
Compressor (18 MPa)	88 - 95	≈ 600 000	20
Compressor (70 MPa)	80 - 91	1 650 000 - 3 300 000	20
Liquefier	≈ 70	7 500 000 - 16 650 000	20

As a simplification, pressurised storage is independent of compression degree, while compression is divided into two pressures. Fuel cell electric vehicles, or FCEVs store hydrogen at 70 MPa to achieve an adequate energy density [Gro]. For large scale, the costs of compression are considered too high to use such compression degrees, so a compression to 18 MPa is more applicable. At 70 MPa and 20 degrees centigrade, hydrogen gas density is approximately 39.72 kg/m^3, while at 18 MPa, the density decreases to approximately 13.38 kg/m^3.

According to a comparison study of hydrates and traditional storage technologies [Pro+09], the following values for various output pressures are acquired and shown in Table 2.5. The required energy is only theoretical, but will serve as a basis for this thesis nonetheless. The values in Table 2.4 and 2.5 are used as input parameters in the optimisation model.

Table 2.5: Storing energy of hydrogen at pressures from 20-70 MPa [Pro+09]

Pressure	Storing energy		
Input $\longrightarrow$ output	[kWh$_{el}$/kWh$_{H_2}$]	[kWh$_{el}$/kg$_{H_2}$]	[kJ/kg$_{H_2}$]
1 MPa $\longrightarrow$ 20 MPa	0.09	3.00	10 800
1 MPa $\longrightarrow$ 35 MPa	0.10	3.33	11 988
1 MPa $\longrightarrow$ 70 MPa	0.12	4.00	14 400

2.4 Fuel Cell Technology

There are several types of fuel cells. Some can only use pure hydrogen, whilst other types can use fuels such as bio-gas since their high operating temperatures enables internal reforming of hydrogen. The common denominator of fuel cells is that all are made up of an anode and a cathode encapsulating an electrolyte. There are positive and negative aspects with all fuel cell types which will be discussed further in this section. Efficiencies are limited to a pure hydrogen-to-electricity efficiency and waste heat regeneration is not considered when choosing fuel cells for the project.

2.4.1 Phosphoric Acid Fuel Cells

Phosphoric acid fuel cells, or PAFCs, operate at around 150-200 degrees centigrade. The technology owes its name to its electrolyte, phosphoric acid. Positively charged hydrogen ions, H^+, move from the anode to the cathode through the electrolyte. Electrons are generated at the anode and travel through an external circuit, providing electric power and return to the cathode. At the cathode, the electrons and hydrogen ions react with oxygen to form water, which is then expelled from the fuel cell. The electrode is helped by a platinum catalyst to speed up the reaction [Ame04c].

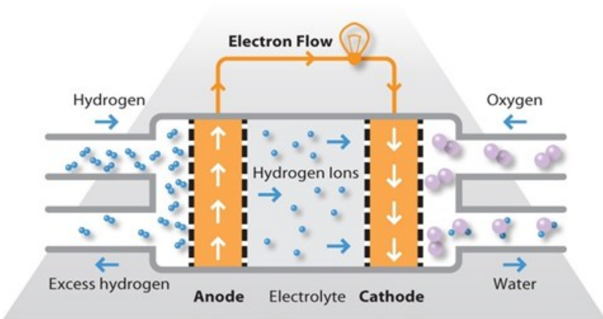


Figure 2.4: Phosphoric acid fuel cell [Fueb]

A common challenge with fuel cells is that carbon monoxide around the electrode can poison the fuel cell. This can happen if the provided hydrogen is impure, but is usually not a problem with electrolysed hydrogen. The problem is more applicable if the hydrogen stream is made from fossil fuels. Nonetheless, PAFCs can handle a carbon monoxide concentration of around 1.5% since their operating temperature is high enough to mitigate the problem. PAFCs efficiency is on average 40-50%, but can be increased to around 87% if heat regeneration is applied [Oku09].

2.4.2 Alkaline Fuel Cells

Alkaline fuel cells, or AFCs, operate at around 150-200 degrees centigrade and typically use a solution of potassium hydroxide, KOH in water as the electrolyte. In AFCs, hydroxyl ions, OH- move from the cathode to anode through the electrolyte. Hydrogen gas reacts with the hydroxyl ions at the anode, which releases electrons and produces water. The electrons move through an external circuit and return to the cathode. The electrons then react with oxygen and water, producing more hydroxyl ions. The hydroxyl ions then diffuse into the electrolyte [Ame09].

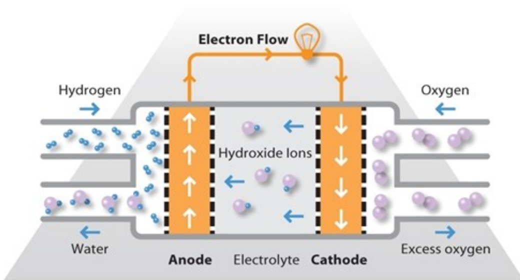


Figure 2.5: Alkaline fuel cell [Fuea]

AFCs require very pure hydrogen even though they operate at the same temperatures as PAFCs. This is because pollutants in the hydrogen stream result in an unwanted chemical reaction that forms solid carbonate inside the cell. The carbonate will interfere with the fuel cell and slow down processes. This is not a problem when hydrogen is produced through water electrolysis, but rather when the hydrogen is supplied from fossil fuels via an external reformer. AFCs operate at around 45-65% efficiency, but can reach 87% with heat regeneration like PAFCs [BKC06].

2.4.3 Polymer Electrolyte Membrane Fuel Cells

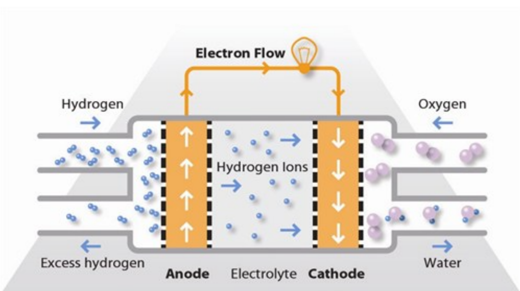


Figure 2.6: Polymer electrolyte membrane fuel cell [Fuec]

Polymer electrolyte membrane, proton exchange or PEM fuel cells use a thin permeable polymer sheet as electrolyte. The membrane enables the fuel cell to operate at as low as 80 degrees centigrade, far lower than other fuel cells. In PEMFCs, hydrogen atoms are ionised at the anode, and the positively charged protons move to the cathode through the membrane. Again, the electrons move through an external circuit and combine with hydrogen protons and oxygen at the cathode to form water. For a PEMFC to work, the polymer sheet must allow hydrogen protons to pass through while prohibiting electrons and other gases to do the same [Ame04b].

PEMFCs require pure hydrogen as fuel because this is the most efficient when using platinum catalysts. It is possible to run PEMFCs when there is carbon monoxide pollution in the fuel, but platinum alloys or ruthenium should then be used to mitigate the carbon monoxide poisoning [BP04]. When operating using high-purity hydrogen, PEMFCs can achieve efficiencies of approximately 60% [LSC20].

2.4.4 Solid Oxide Fuel Cells

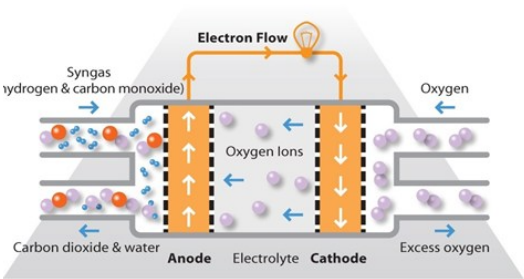


Figure 2.7: Solid oxide fuel cell [Fued]

Solid oxide fuel cells, abbreviated SOFCs, utilise a non-porous ceramic compound, a mixture of zirconium oxide and calcium oxide, to form a crystal lattice to serve as the electrolyte. SOFCs operate at temperatures up to 1 000 degrees, removing the need for an external reformer. This also increases start-up time. Negatively charged oxygen ions are supplied at the cathode and move through the electrolyte while a hydrogen-rich gas passes over the anode. The negatively charged oxygen ions oxidise the fuel, and electrons generated at the anode travel through an external circuit.

As mentioned, the high operating temperatures of SOFCs remove the need for an external reformer but at the cost of longer start-up times. This is the major drawback of this fuel cell technology, but SOFCs can still operate with electrical efficiencies upwards of 60%, matching PEMFCs. SOFCs are typically used in stationary power generation where heat recovery can be used to increase the efficiency to around 85% [Ame04a].

2.4.5 Comparison of Fuel Cell Technologies

The theoretical maximum efficiency of a fuel cell can be calculated by applying the Gibbs free energy of H_20, ΔG_{f° [Lum] and the higher heating value of hydrogen, HHV_{H_2}, resulting in an efficiency of 83% at 298K as shown in Equation 2.4 [Kho19] [NRE].

$$\eta = \frac{\Delta G_{f^\circ}}{\Delta H} = 1 - \frac{T\Delta S}{\Delta H} = 0.82959 \tag{2.4}$$

Where $\Delta G_{f^\circ} = -237.13\,kJ/mol$ and $\Delta H = -285.83\,kJ/mol$

Whether efficiencies close to the theoretical maximum are possible depends on many factors, including internal resistance losses, but this will not be investigated further in this thesis. It does, however, provide some leeway when doing sensitivity analyses of the results from the optimisation model.

As of 2015, AFCs are the most cost-efficient fuel cell technology when considering CAPEX at approximately 1 650 - 5 800 NOK/kW. Following AFCs are PEMFCs and SOFCs at around 24 900 - 33 200 NOK/kW and PAFCs at around 33 200 - 41 500 NOK/kW [IEA15]. Although there are vast differences in investment costs, there are other important factors to consider as well. The lifetime and efficiency of the fuel cells is just as critical as cost per kW. When deciding what technology to choose, what really is important is cost per hour of capacity. Output pressure should also be considered as it is more cost efficient to increase the pressure inside the cell than with an external compressor. Table 2.6 summarises the fuel cell comparison. The specific cost is calculated with Equation 2.5, giving a cost per 1 000 hour of capacity while considering the efficiency of the cell as well.

$$C_{specific} = \frac{CAPEX \cdot 1000\,h}{t_{life} \cdot \eta} \tag{2.5}$$

	Efficiency [%]	CAPEX [NOK/kW]	Lifetime [h]	Specific cost
AFC	45-65	1 650 - 5 800	5 000 - 8 000	317.31 - 2577.78
PEMFC	60	24 900 - 33 200	60 000	691.67 - 922.22
SOFC	60	24 900 - 33 200	$<$ 90 000	461.11 - 614.81
PAFC	40-50	33 200 - 41 500	30 000 - 60 000	1106.67 - 3458.33

Table 2.6: Comparison of fuel cell technology

Based on the specific cost of fuel cells, operating temperature, and subsequently the start-up time, PEM is chosen as the technology for this thesis' optimisation model. Although investment costs for SOFCs are lower, a P2G system must be able to quickly adapt to varying electricity prices and the low operating temperature of PEMFCs also allows for more freedom in designing the plant (considering hydrogen's autoignition temperature).

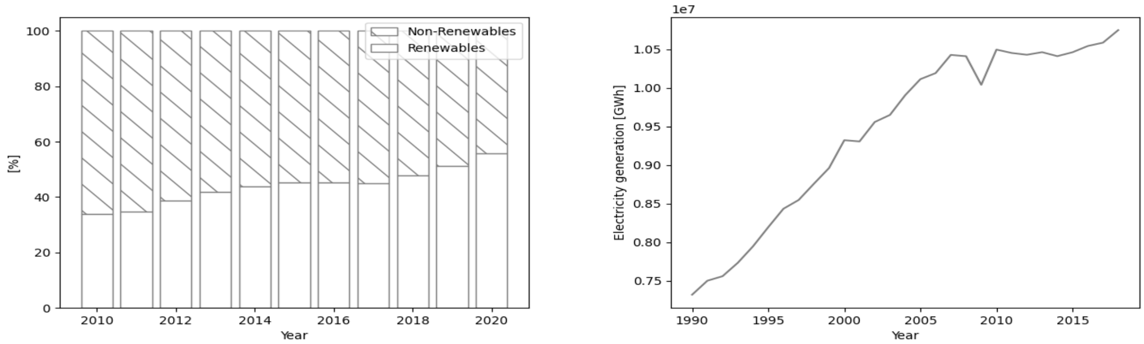
Assuming the same learning curves for PEMFCs as for PEMECs, the predicted costs can also be calculated. The predicted values, although with simplifications, are shown in Table 2.7. It is in this thesis assumed that cost decrease linearly with time due to learning curves, translating to a cost reduction of approximately 2.3% per year based on the price decrease of electrolysers found in Section 2.2. This results in the following cost projections, shown in Table 2.7. It should be noted that these projections are not investigated to a large extent and is just used to see how the future might look for P2G systems.

Table 2.7: Learning curves' effect on PEMFCs

	PEMFC				
Efficiency [%]	Low		Med		Max
	50		60		83
Capacity cost	2015	2020	2030	2040	2050
[NOK/kW$_{el}$]	24900-33200	22000-29350	16200-21600	10400-13850	4600-6100

2.5 Electricity Market Trends

In OECD countries, fossil fuels remained the major contributor to electricity production in 2020, making up 44.3% of the total production volume. Although fossil fuels have been the main source of electricity in the OECD, renewables have been steadily increasing and are now responsible for 55.7% of the total electricity production, with hydro, wind and solar being responsible for 23.2%, 18.3% and 6.3%, respectively. As shown in Figure 2.8a, the proportion of green electricity in the supply chain has been steadily increasing and is expected to increase further.



(a) Yearly distribution between renewables and non-renewable electricity sources in OECD Europe, 2010-2020, [IEA21a]

(b) Total electricity production in OECD countries, 1971-2019, [OEC21]

Figure 2.8: Total electricity production and distribution between renewables and fossil fuels

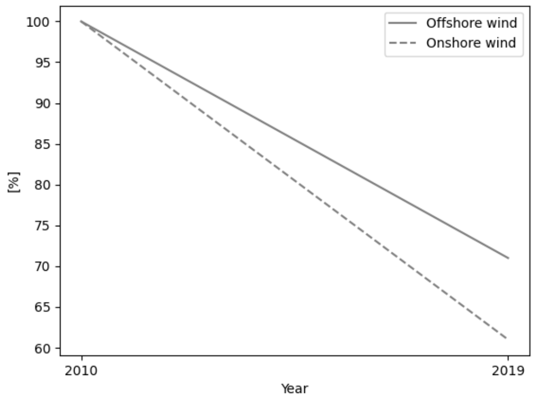
Figure 2.8b shows the development of the OECD countries' total electricity production since the 1990s. There has been a steady increase due to an increased standard of living and a larger population. The data is limited to the time span between 1990-2018 since this was the best available data. This is because of several factors, one being that data from autoproducers was unavailable for most of the period. Additional sources of electricity have been added continuously, but the data from 1990 covers most of them. The drop in 2009 is due to changes in the reporting methodology. Electricity production is defined as electricity generated by burning fossil fuels, nuclear energy, wind, solar, etc. The electricity production data includes both data from main activity producers* and autoproducers**. Figure 2.8b shows a clear increase in electricity production, with an increase of approximately 1/3 from 1990 to 2005, but the rate of increase has declined after 2009. This might be because of a change of habit, but more likely because of the changes in the reporting methodology.

*Main activity producers produce electricity for export to third parties

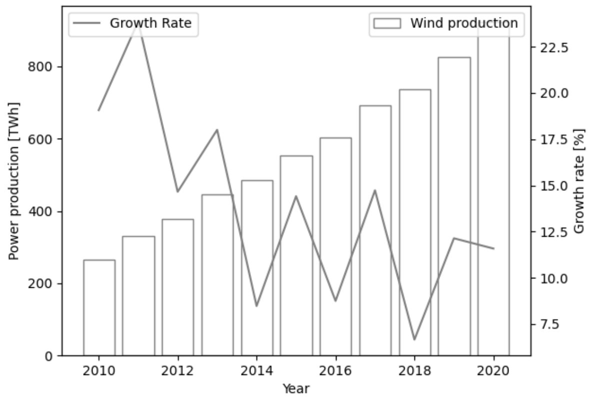
**Autoproducers produce electricity mainly for own consumption

2.6 Wind Power Market Trends

Due to increasingly competitive supply chains, economies of scale and technological advancements, wind power has seen a steady decrease in costs over the past decade. According to IRENA [IRE20], the cost of onshore and offshore wind has decreased by 47% and 39%, respectively, from their 2010 levels with no sign of abating. This is illustrated in Figure 2.9a, albeit only showing the development linearly and not the year-on-year decline. Although the COVID-19 pandemic has thoroughly impacted the economies of the world, renewable power generation was predicted to continued to grow in 2020, something which turned out true when looking at Figure 2.9b.



(a) Cost decline for offshore and onshore wind power, 2010-2019 [IRE20]



(b) Yearly wind production and growth rate in OECD countries, 2010-2020 [IEA21b]

Figure 2.9: Graphs illustrating wind power market trends

As expected, the wind production rate increases with decreasing costs. This has been the trend during the last decade, although with varying year-on-year growth rate. Figure 2.9b shows how the total wind production has close to quadrupled in the OECD countries during the last 11 years, with an average growth rate of just short of 14%.

In recent years, offshore wind has shown itself as a possibility to expand the wind power market to provide clean energy to areas where the wind potential is high and the available land area is limited, both due to logistics as well as politics. Offshore wind energy has both pros and cons. Moving turbines offshore generally results in higher wind speeds, larger turbines and less impact on nature, although the latter is a whole discussion in itself. On the other hand, offshore wind turbines are more cost intense, can have longer downtime periods and transportation emissions and costs are higher than that of onshore.

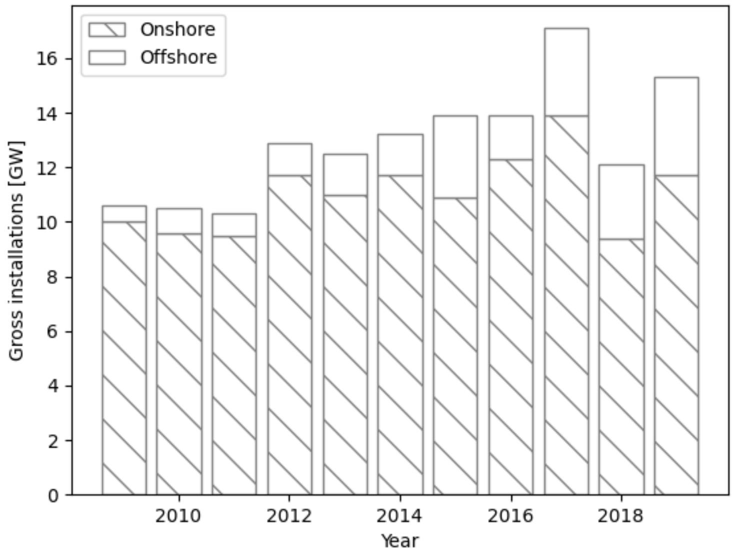
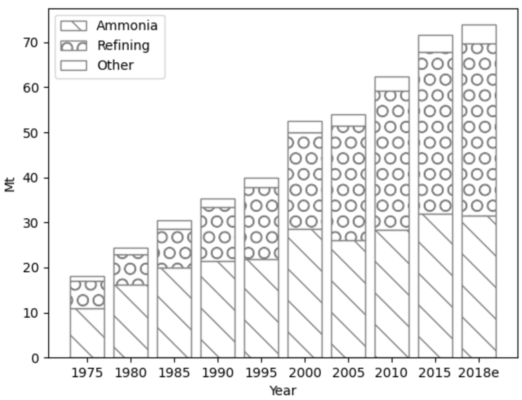


Figure 2.10: New annual onshore and offshore wind installations in Europe [Eur21]

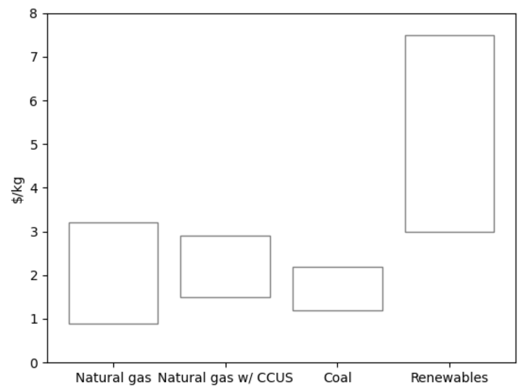
Figure 2.10 shows that onshore wind by far is the biggest contributor to wind power production, but offshore wind being responsible for an increasing share of the total production. According to GlobalData Energy [Ene21], offshore wind production is expected to surpass onshore wind around the turn of the next decade.

2.7 Hydrogen Market Trends

Hydrogen demand has more than tripled since the 1970s and is becoming a large market worldwide. Hydrogen production is almost exclusively produced from non-renewable fossil fuels, accounting for 6% of the natural gas and 2% of the worlds coal consumption. This results in major emissions of CO_2, totalling roughly 900 million tonnes per year. To put this in perspective, it is equivalent to more than the carbon emissions of the UK, France and the Netherlands combined [OWD20]. Figure 2.11a shows the distribution of hydrogen demand between industries. The graph shows clearly that ammonia and refining account for almost all hydrogen consumption with approximately 95%, while the remainder is distributed between various industries like transportation.



(a) Global hydrogen demand [Mt] [IEA19]



(b) Hydrogen production costs, 2018 [IEA18]

Figure 2.11: Graphs illustrating hydrogen market trends

As shown in Figure 2.11b, green hydrogen remains the more cost intense production method to date. This is expected to decrease in the coming years as electrolysers and wind power will become more efficient and affordable while taxing of carbon emissions will increase. Green hydrogen has a production cost between $3-8 per kg, translating to approximately NOK 750 - 1 750 per kWh. Grey hydrogen costs are lower than the lowest values for green hydrogen. Subsequently, green hydrogen costs have to approach the costs of grey hydrogen to become a more dominant market.

In 2050, it is estimated that the energy sector will consume a total of 19 exajoule of hydrogen. Converted, this is approximately 700 GW of installed electrolysis capacity by 2030 and 1700 GW by 2050. Considering economies of scale and previous learning curves, the electrolysis capacity costs are expected to decrease to approximately NOK 3 100 per kW by 2050 [Wen00]. While costs for electrolysis are expected to decrease, natural gas reforming is expected to increase, although not as drastically.

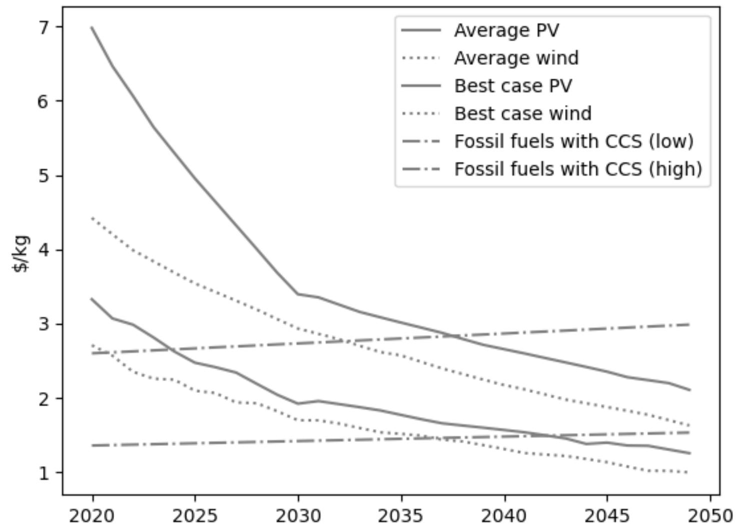


Figure 2.12: Hydrogen production cost predictions, 2020-2050 [IRE19]

Hydrogen production from wind and solar projects is expected to be cost-competitive within the next five years at the earliest compared with natural gas reforming with carbon capture and storage. As shown in Figure 2.12, by 2040, all green hydrogen production methods are expected to be cost-competitive compared to fossil fuel alternatives. It is worth mentioning that the calculations behind Figure 2.12 does not consider changes in costs of carbon capture, potentially skewing the results. The costs in Figure 2.12 will be used as a basis during the optimisation section in this thesis.

Chapter 3

Methodology

The methodology will explain how data is analysed and simulated, used to produce useful input data, and ultimately how the optimisation model is built. Section 3.1 explains how the thesis is limited and what the overall aim of the optimisation problem is. Section 3.2 explains how the model is built and how it uses the different input data. Section 3.3 covers the use of Markov Chains in simulating time series data based on historical data and how the simulated data compares to historical data. Section 3.4 shows how the power curve is generated and how it is used in tandem with wind data to calculate electricity production. Wind and spotprice data is also covered in this section. Section 3.6 shows how the optimisation model is defined and covers what parameters and constraints are used.

3.1 Limitations and Scope

Before simulating wind speeds using Markov chains, historical wind data will be decomposed and analysed. The power curve is based on a known power curve for the GE Haliade-X 220 12, but as a simplification, cut-in and cut-off are assumed instantaneous. Spotprices are simulated using Markov chains based on historical price data from Nordpool [Nor20]. To cope with Markov chains' lack of seasonal simulation capabilities, the data for both wind speeds and spotprices are separated into monthly data to force the simulation to handle seasonality, albeit rather rudimentary. This study does not cover the costs of wind turbines and other infrastructure, as the primary objective is to see if a P2G system increases profitability. The costs of fuel cells, compressors, electrolysers and storage are the only costs that are considered. Costs are included both as capacity costs as well as operational costs, e.g. maintenance, stack replacements, etc. The most important limitations of the methodology are shown below.

- Data is simulated using Markov chains
- Seasonality is handled by grouping data into monthly data
- Wind farm costs are not covered

In the optimisation model, it is assumed that the grid is always able to import electricity from the wind farm, i.e. the electricity market is assumed to be unaltered by the wind farm. Transportation costs are not considered as it is assumed that a third party purchases hydrogen and electricity directly from the farm and is responsible for transportation, e.g. power lines, pipelines, vessels, etc. The optimisation is limited to a single year, as the model is purely theoretical and is used to see how seasonal variations impact the profitability of the system. The most important limitations of the optimisation are shown below.

- Output from the wind farm does not affect the electricity market, i.e. closed system
- Transportation costs are not considered
- Optimisation is limited to 1 year or 8760 hours
- Costs are assumed constant during optimisation, while spotprices and wind speeds vary

3.2 System Description

The system in this thesis consists of wind turbines, electrolysers, compressors and storage solutions. A rudimentary visualisation of the optimisation model's process is shown in Figure 3.1 below. This diagram can be broken down, and each process can be further described, which the optimisation model will do. The process involves three inputs; spotprice, hydrogen price and wind speed. The system uses this information to make decisions whether to produce pure electricity, hydrogen or a combination of the two. This information could also be used to make predictions on spotprices to decide if hydrogen should be stored and converted to electricity if spotprices are predicted to increase significantly at a later time.

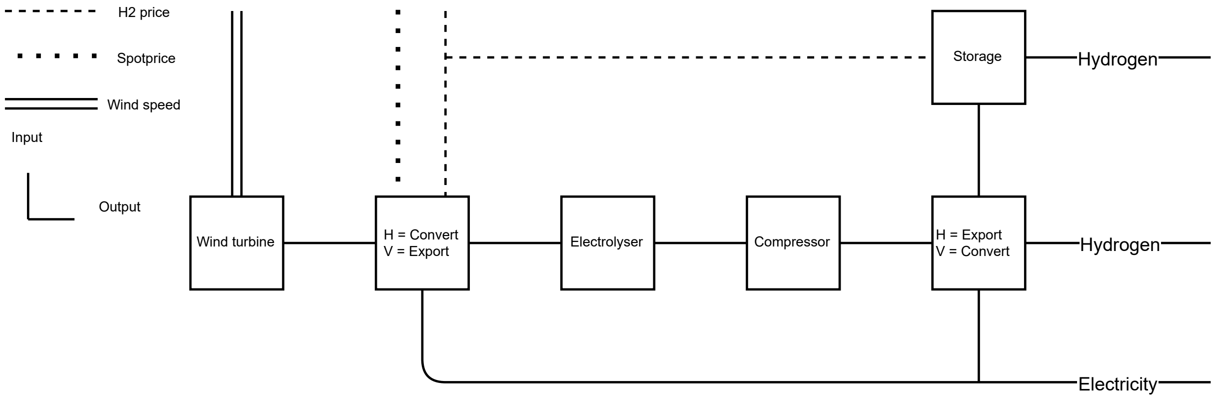


Figure 3.1: A visual representation of the optimisation model's process

3.3 Markov Chains

A discrete-time Markov chain is a stochastic process comprising a finite number of transition probabilities and states, moving through successive time periods. In this thesis, a first-order Markov chain is chosen, meaning that the conditional probability distribution is only dependent on the current state of the system and not previous states. This is a simplification that is useful when there is not enough viable data to sufficiently model probabilities based on multiple previous states. A first-order Markov chain is therefore considered to be *memory-less*. Markov chains can be applied to a wide variety of problems, be it physics, medicine, economics and many others, making it a good foundation for prediction of both electricity prices as well as wind speeds. One drawback of using Markov chains, though, is that the forecasting method does not consider seasonality. This is handled to a certain degree by separating the forecasting into monthly data, meaning data from month x does not affect data from month y [Che14].

3.3.1 Markov Chain States

To forecast data using Markov chains, the first step is to divide the data into states. The optimal number of states can vary due to, for instance, the amount of available data or the amount of data points within each state. Subsequent to acquiring the data needed and when the state range has been set, the Markov chain states can be expressed using a vector. This is shown in Equation 3.1 below.

$$states = \begin{bmatrix} P_i \\ \vdots \\ P_j \end{bmatrix} \tag{3.1}$$

3.3.2 Transition Probability Matrix

When the states have been set, the next step is to create a transition probability matrix. This matrix is used to express the probability of moving from state i to state j. A first-order Markov chain is, as mentioned earlier, memory-less. Thus, the probability transition matrix is, along with the set states, the only thing that is needed to successfully forecast data using this method. A generic probability transition matrix is shown in Figure 3.2 below:

$$Probability\ matrix = \begin{bmatrix} P_{ii} & \cdots & P_{ij} \\ \vdots & \ddots & \vdots \\ P_{ji} & \cdots & P_{jj} \end{bmatrix} \tag{3.2}$$

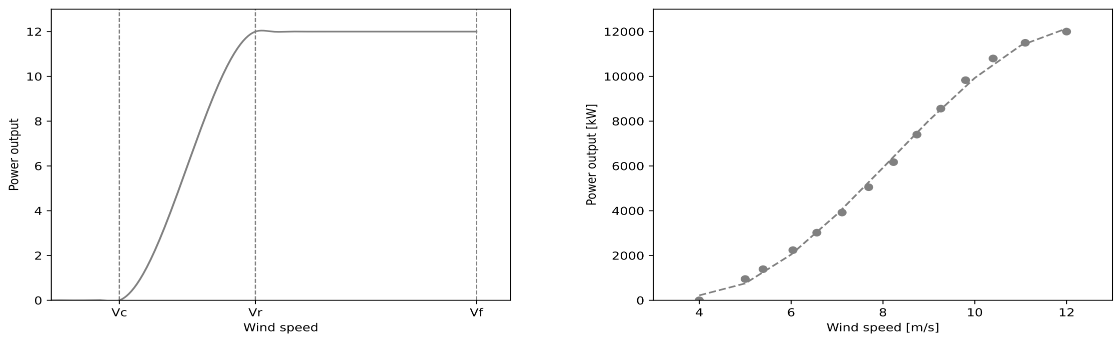
Now, using the states and transition probabilities for each month, forecasting of spotprices and wind speeds can be simulated using a Markov chain Matlab script supplied from the course *TMR12 Ocean Systems Simulation* at NTNU. This data is later used as input for the optimisation model in Section 3.6.

3.4 Power Production

To evaluate whether or not offshore hydrogen production can be beneficial from a purely monetary perspective as well as a way of storing energy, there are several areas that need investigating. First of all, a power curve for the chosen turbine has to be acquired.

3.4.1 Power Curve

A power curve is a graph indicating how much electric power production one can expect for a given turbine at a given wind speed. A power curve also shows what the cut-in and cut-out speed, v_c and v_f respectively, are, as well as rated output speed v_r is. This is illustrated through a generic power curve in Figure 3.2a below.



(a) A generic power curve

(b) Non-rated area of GEHX12

Figure 3.2: Power curves

In this thesis, the GE Haliade-X 220 12, henceforth known as GEHX12, is chosen as it has one of the highest-rated power outputs on the market currently [Ele]. Power curves are made using local field measurements using an anemometer, but is in this thesis naturally constructed using coding. Since v_c, v_f and the rated region of the GEHX12 are known, the non-rated region has to be found. GE were reluctant of supplying data for the power curve, but by using an image of the graph and DigitizeIt [Bor21], the data points were acquired. v_c, v_f and the rated region are handled using Algorithm 1, while the non-rated region is handled using a 3^{rd} order polynomial shown in Equation 3.3. Equation 3.3 is made using curve fitting in Python.

$$-40.15v^3 + 979.77v^2 - 5835.47v + 10455.36 \tag{3.3}$$

Algorithm 1 Power production

if $v < v_c$ **then**

$p = 0$

else if $v > v_f$ **then**

$p = 0$

else if $v_c >= v >= v_r$ **then**

$p = Equation\, 3.3$

else

$p = p_r$

end if

3.4.2 Wind analysis

After the power curve equation is created, the available wind energy has to be analysed and simulated. There are several methods of simulating wind, but as mentioned, Markov chains will be used in this thesis. As this thesis' objective is to determine profitability of wind power hydrogen production in general, a somewhat arbitrary location in the North Sea was chosen. The raw wind data is downloaded from Copernicus [Cop21]. The results of the wind analysis is considered part of the methodology and not results as it is used in the optimisation model to acquire the preferred results.

3.4.2.1 Seasonal Decomposition

Firstly, breaking the wind data into different components is helpful to locate any patterns in the wind data. By doing seasonal decomposition of wind data in the chosen area, the wind speed can be broken down into *trend*, *seasonality* and *residuals*. This is shown in Figure 3.3 below.

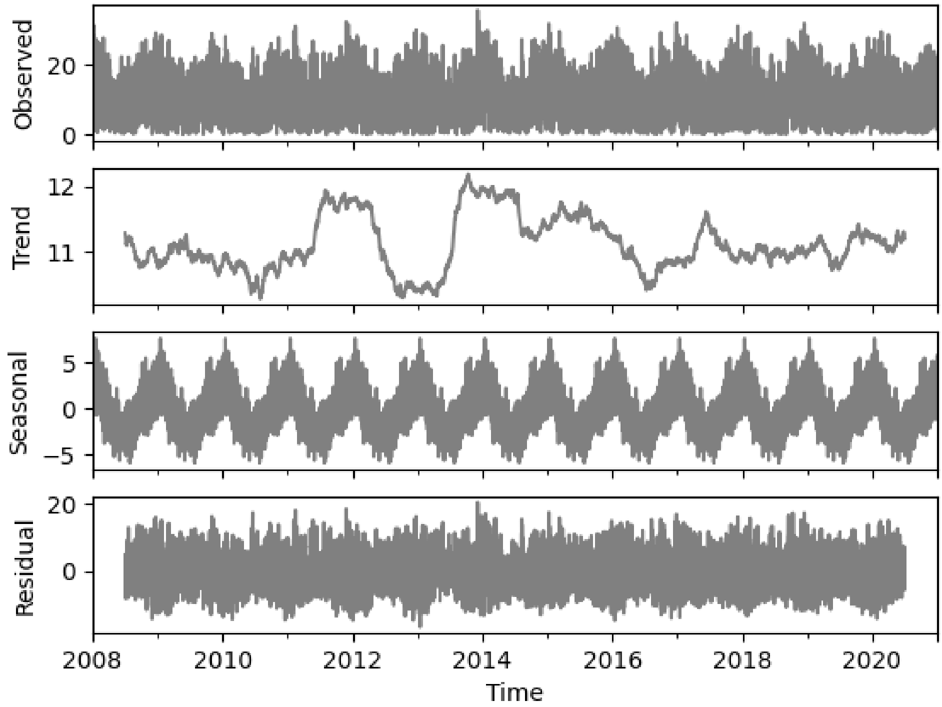


Figure 3.3: Seasonal decomposition of wind data between 2008 and 2020 for location in the North-Sea

The topmost graph shows the observed data, while the other three show trend, seasonality and residuals, respectively. The observed wind data show slight sine-tendencies with peaks around the turn of every new year. When broken down, the sine-tendencies are more defined. This is clearly shown in the seasonality graph with a period of one year, peaking around the turn of every new year. This fits well with the understanding that wind forces are greater in the winter months in the northern hemisphere due to increased pressure difference between air masses [Log19]. Markov chains are unable to handle seasonality. As a countermeasure, the wind data is grouped into monthly data before simulation to force the script to handle seasonality. The data is then simulated per month and the simulated data is put together to form an entire year. As mentioned earlier, the data is a modified Matlab script from *TMR12 Ocean Systems Simulation.*

3.4.2.2 Distribution

The wind data is scaled with wind speed extrapolation in accordance with the power law [MMR09], shown in Equation 3.4. The scaled data is then used to create a histogram and a probability matrix showing the probability of moving from one wind state to the next. These are both shown below in Figure 3.4a and 3.4b, respectively.

$$v_2 = v_1 \cdot (\frac{z_2}{z_1})^{\alpha} \tag{3.4}$$

v_1 : *velocity at height* z_1

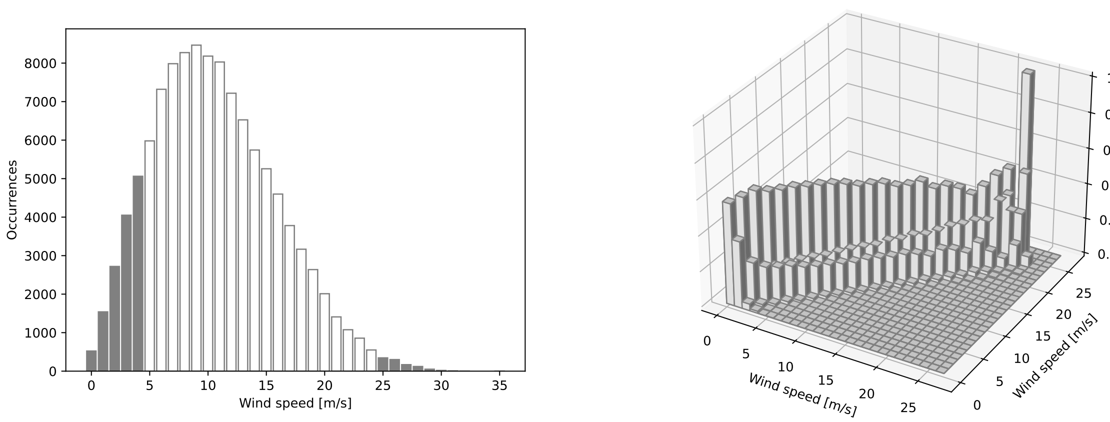
v_2 : *velocity at height* z_2

z_1 : *height* 1 (*lower*)

z_2 : *height* 2 (*upper*)

α : *wind shear exponent*

In Figure 3.4a, the wind speeds able to generate power using GEXH12 are shown in white color. The grey areas are values below the cut-in speed and above the cut-of speed.



(a) Histogram of wind states from 2008-2020

(b) Probability matrix of wind speeds from 2008-2020

Figure 3.4: Wind data characteristics 2008-2020

Figure 3.4b shows the transition probability matrix for the input data. The data is mostly in a close vicinity of the diagonal, in line with basic probability theory. Using the data from Figure 3.4b, wind speeds can be simulated using Markov chains. The simulated wind speeds are shown in Figure 3.5 below.

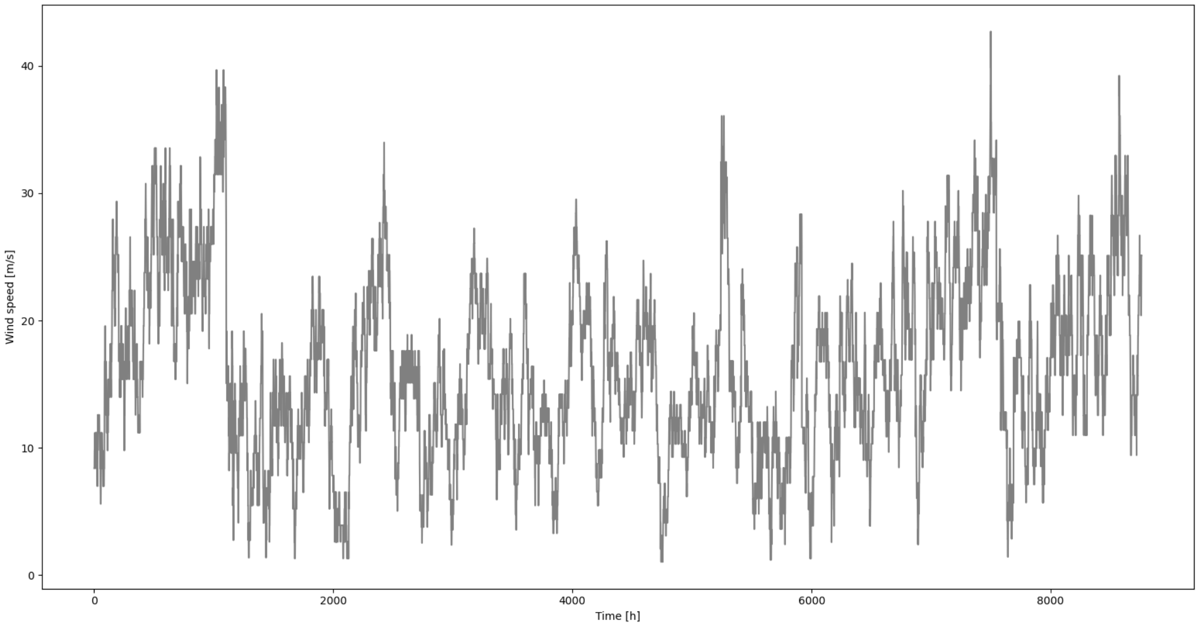
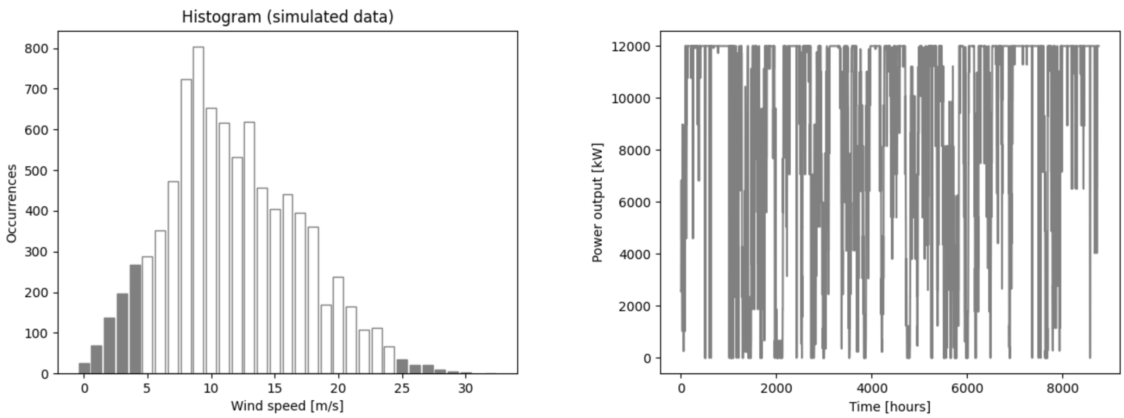


Figure 3.5: A year of simulated wind speeds

3.4.3 Power output

Using the power curve created in Section 3.4.1 along with wind data simulated in Section 3.4.2, the power output can be calculated using a Python script. Figure 3.6a shows the distribution of wind speeds from the simulated data. As mentioned in Section 3.4.1, the GEHX12 is limited to produce electricity between a range of wind speeds. Both below 4 m/s and above 25 m/s, the wind turbines will either not be able to produce electricity efficiently, or the wind forces will be too severe, and the turbines will have to shut down to not damage the turbines. White bars represent wind speeds where the turbines are able to produce electricity, while the grey bars represent the wind speeds that result in the turbines shutting down. The resulting power production is shown in Figure 3.6b. The figure suggests that power production generally either is in the rated region or zero. In fact, the turbine is at peak production about 49.2% of the time.



(a) Histogram of simulated wind data

(b) Power production

Figure 3.6: Power production analysis

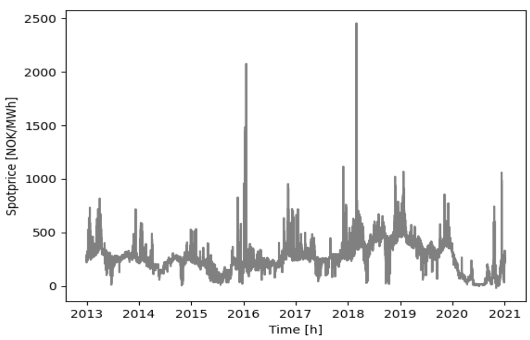
Using Figure 3.6a, it is also possible to calculate the maximum potential uptime for the wind park. The simulated data would in a perfect world result in an uptime of 86.92%, about 4% lower than what the measured data would suggest (90.99%). Whether this will affect the results significantly is still yet unknown, but will be assessed during the optimisation. The power output is exported as a time series and later used in the optimisation model.

3.5 Economics

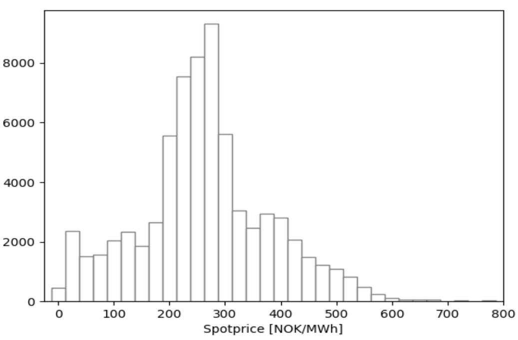
The following sections will analyse input values for spotprices and simulate a time series of predicted spotprices. The data will be qualitatively analysed and key information about the differences will be provided. Later, net present value will be discussed and a generic example will be shown. The results of the spotprice analysis is considered part of the methodology and not results as it is used in the optimisation model to acquire the preferred results.

3.5.1 Spotprice analysis

As mentioned in Section 3.3, using historical data measured over several years, a fairly accurate transition probability matrix can be made and used to simulate a year of spotprice data. The model uses data collected from Nordpool [Nor20] over eight years, from 2013 to 2020. This is then used to create a transition probability matrix. A simulated year of spotprices is then visualised using a script not included in this thesis, illustrated by Figure 3.7a. As mentioned earlier, Markov Chains cannot handle seasonality, but this is considered when modelling the data by dividing the input data into monthly data rather than an eight-year period. Figure 3.7b shows the distribution of spotprices for the input data. The histogram is limited to a max price of 800 NOK/[MWh] for illustrative purposes, as there are a few occurrences of really high values. The Markov model, on the other hand, uses the entire spectrum.



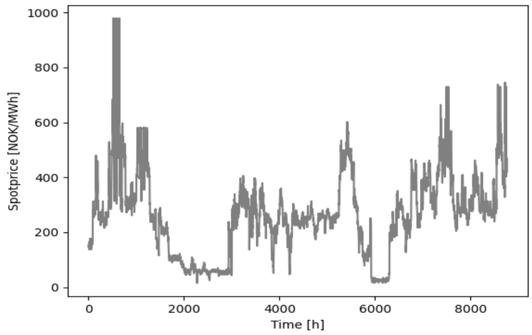
(a) Time series of spotprices, 2013-2020



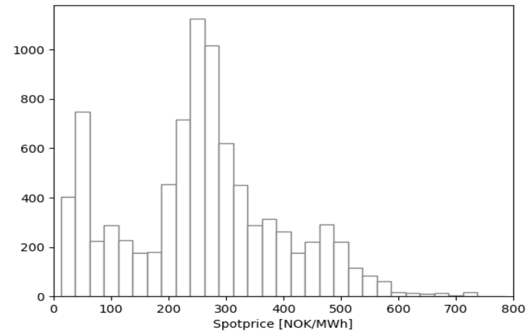
(b) Histogram of spotprices, 2013-2020

Figure 3.7: Spotprice characteristics, 2013-2020

Using what is stated above, a time series of spotprices is simulated. Figure 3.8a shows the simulated time series, while Figure 3.8b shows the distribution of spotprices.



(a) Time series of spotprices, 2013-2020



(b) Histogram of spotprices, 2013-2020

Figure 3.8: Spotprice characteristics, 2013-2020

As explained, the model is forced to handle seasonality by dividing up the datasets. Nonetheless, there are some parts of the plot that stand out. This is from approximately 5 900 hours in the simulated data (Figure 3.8a), where the spotprices are locked within a relatively narrow range for about 400 hours. This can be explained by the fact that the input data is divided into *state ranges* and that much of the data is within a few state ranges, resulting in really high probabilities of alternating between two states. This phenomenon also appears in the measured data (Figure 3.7a) from around 65 000 hours to around 67 000 hours, making the simulated data look more applicable. The simulated data does not reach as high values as the measured data, but this is purely down to the fact that the probability of these high prices occurring is very low. Since the model is based on a probability matrix, it is unlikely to happen during such a brief time span, but if data is simulated for several years, the probability of these prices occurring increases significantly. The mean values of the two plots are very similar, being 264.39 and 260.96 for measured and simulated data, respectively. This is the equivalent of a 1.3% decrease from the measured to the simulated data.

Using this data, the optimisation model will be able to take action per time step to maximize the profit from the power-to-gas system. A possible advantage of simulating the electricity and hydrogen prices is that the optimisation model could be able to continuously predict both the price of hydrogen and of electricity several time steps ahead. This will enable the system to decide if or when to store hydrogen for future export or conversion, increasing profitability. This will not be handled in this thesis, but could be a potential for further work.

3.5.2 Net present value

Net present value is the difference between the present value of cash in- and outflows over a specified period of time. NPV is often used in planning and analysing of project investments. In layman's terms, NPV is used to determine today's value of a future investment. The discount rate is defined as the percentage an investor demands in minimum return on a project. In this thesis, NPV will be used to assess the value of yearly income to determine what affects the value of a P2G system the most. A downside of using NPV is that it will make assumptions of the future that the person performing the analysis is unable to predict to a 100% certainty. The formula for calculating NPV is shown in Equation 3.5 below.

$$NPV = \sum_{t=0}^{T} \frac{R_t}{(1+i)^t} \tag{3.5}$$

In this thesis the discount rate is set to 7.5% as this is the average value for offshore wind according to IVSC [Fre21]. As shown in Figure 3.9, the NPV decreases over time as the cash flow's value decreases. A cash flow with a discount rate of 7.5% looses half of its original value after approximately 9-10 years.

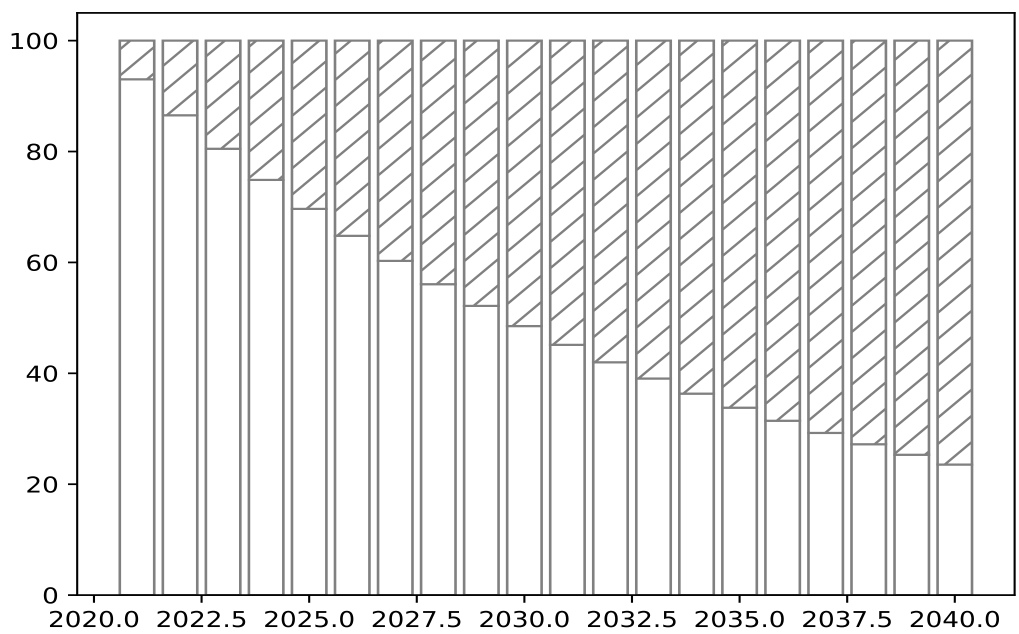


Figure 3.9: An example of NPV calculations over a period of 20 years

3.6 Optimisation

The optimisation model's objective is to maximise the profit of wind farms by utilising low power demand periods during operation. Hydrogen will be produced using polymer electrolyte membrane electrolysis, stored if electricity prices are expected to increase in the future and converted back to electricity using fuel cells based on the same technology. The optimisation model will determine the optimal configuration of fuel cells, electrolysers and storage to maximise the profit. The benchmark, only exporting electricity will form the baseline for further calculations, where the model maximises the profits above this value. The input parameters of the model are a variation of time series and constant values, where the constant values are acquired from trustworthy sources, while the time series are simulated based on multiple years of historical data.

Sets:

T	Number of time steps, indexed t	

Parameters:

C_t^e	Spotprice at time t	[NOK/MWh]
C^{H2}	Hydrogen price at time t	[NOK/MWh]
A_t^e	Available power at time t	[MWh]
η_{ec}	Efficiency electrolyser	[-]
η_{fc}	Efficiency fuel cell	[-]
η_c	Efficiency compressor	[-]
C_c^{fc}	Capacity cost fuel cell	[NOK/MW]
C_c^{H2}	Capacity cost hydrogen storage	[NOK/MW]
C_c^{ec}	Capacity cost electrolyser	[NOK/MW]
C_c^c	Capacity cost compressor	[NOK/MW]
C_o^{fc}	Operational cost fuel cell	[NOK/MW]
C_o^{H2}	Operational cost hydrogen storage	[NOK/MW]
C_o^{ec}	Operational cost electrolyser	[NOK/MW]
C_o^c	Operational cost compressor	[NOK/MW]
P_{ec}^{min}	Minimum capacity electrolyser	[MW]
P_{fc}^{min}	Minimum capacity fuel cell	[MW]
P_c	Power consumption compression	[MWh]
P_w	Water consumption	[kL/MWh]
C^w	Water cost	[NOK/kL]

Decision variables:

x_t^{ex}	Power export to grid at time t	[MWh]
x_t^{rH2}	Electricity export from fuel cell at time t	[MWh]
x_t^{ec}	Power consumption from electrolyser at time t	[MWh]
x_t^{H2x}	Hydrogen export at time t	[MWh]
v_t^{H2}	Hydrogen storage level at time t	[MWh]
p^{H2}	Power capacity, storage capacity	[MWh]
p^{fc}	Power capacity, fuel cell	[MW]
p^{ec}	Power capacity, electrolyser	[MW]
p^{c}	Power capacity, compressor	[MW]
δ_t^{ec}	Binary variable	[-]
δ_t^{fc}	Binary variable	[-]

Objective function:

$$\begin{aligned} maxZ = &\sum_{t=1}^{T} C_t^e(x_t^{ex} + x_t^{rH2}) + \sum_{t=1}^{T} C^{H2}x_t^{H2x} - p^{ec}(C_c^{ec} + \frac{1}{8760}\sum_{t=1}^{T} C_o^{ec}) \\ &-p^{H2}(C_c^{H2} + \frac{1}{8760}\sum_{t=1}^{T} C_o^{H2}) - p^c C_c^c - \sum_{t=1}^{T} C_t{}^e P_c(v_t^{H2} - v_{t-1}^{H2}) \\ &-p^{fc}(C_c^{fc} + \frac{1}{8760}\sum_{t=1}^{T} C_o^{fc}) - \sum_{t=1}^{T} C^w P^W x_t^{ec}\eta_{ec} \end{aligned} \tag{3.6}$$

The objective function pursues to maximise the system's revenue. The model summarises electricity and hydrogen export income while subtracting capacity and operational costs of electrolysers, water, fuel cells, compressors and storage. This enables the model to define the optimal system configuration and its increased profit. The export of pure electricity serves as the baseline for further analyses as any values above this are considered as an increase in profitability. The result of the optimisation model is therefore the revenue of the total system minus costs of hydrogen production. The cost of electricity production is not investigated as it is considered to be outside of the scope of this thesis.

Due to limitations in hardware, specifically RAM on the computer that was used, the optimisation is not possible to run for 20 years (the lifetime of the electrolysers). As a simplification, this is handled by reducing the capacity cost to represent the cost for one year. The revenues and costs are then used to calculate the net present value for the whole period.

Constraints:

c1	$x_t^{ex} + x_t^{ec} \leq A_t^e$	$\forall\, t \,\epsilon\, T$
c2	$x_t^{ec} \leq p^{ec}$	$\forall\, t \,\epsilon\, T$
c3	$x_t^{ec} \leq M(1 - \delta_t^{ec})$	$\forall\, t \,\epsilon\, T$
c4	$P_{min}^{ec} - x_t^{ec} \leq M\delta_t^{ec}$	$\forall\, t \,\epsilon\, T$
c5	$x_t^{rH2} \leq \eta_{fc} p^{fc}$	$\forall\, t \,\epsilon\, T$
c6	$x_t^{rH2} \leq M(1 - \delta_t^{fc})$	$\forall\, t \,\epsilon\, T$
c7	$P_{min}^{fc} - x_t^{rH2} \leq M\delta_t^{fc}$	$\forall\, t \,\epsilon\, T$
c8	$x_t^{rH2} \geq P_{min}^{fc}$	$\forall\, t \,\epsilon\, T$
c9	$v_{t-1}^{H2} + (x_{t-1}^{ec}\eta_{ec}\eta_c) - \frac{x_{t-1}^{rH2}}{\eta_{fc}} - x_{t-1}^{H2x} = v_t^{H2}$	$\forall\, t \,\epsilon\, T \backslash \{1\}$
c10	$v_t^{H2} \leq p^{H2}$	$\forall\, t \,\epsilon\, T$
c11	$\frac{x_t^{rH2}}{\eta_{fc}} + x_t^{H2x} \leq v_t^{H2}$	$\forall\, t \,\epsilon\, T$
c12	$x^{ex}, x_t^{rH2}, x_t^{ec}, v_t^{H2}, p^{ec}, p^{fc}, p^{H2}, p^c \geq 0$	$\forall\, t \,\epsilon\, T$
c13	$v_t^{H2} - v_{t-1}^{H2} \leq \eta_c p^c$	$\forall\, t \,\epsilon\, T \backslash \{1\}$

Constraint 1 states that the amount of exported electricity and power consumption of the electrolyser at time t is limited by the available power production at time t.

Constraint 2-4 limits the electrolysers consumption to values between the minimum operating capacity and the power capacity of the electrolyser.

Constraint 5-8 implements the same constraints for the fuel cell system.

Constraint 9 defines that the sum of the storage level, v_{t-1}^{H2}, electrolysed and compressed hydrogen, $x_{t-1}^{ec}\eta_{ec}\eta_c$ minus exported electricity from the fuel cell, $\frac{x_{t-1}^{rH2}}{\eta_{fc}}$ and exported hydrogen, x_{t-1}^{H2x} at *t - 1* is equal to the storage level, v_t^{H2} at time t.

Constraint 10 limits the storage level at time t, v_t^{H2} by the power capacity of the storage, p^{H2}.

Constraint 11 limits electricity export from the fuel cell and exported hydrogen by the storage level at time t, v_t^{H2}.

Constraint 12 defines non-negativity for the variables.

Constraint 13 states that the capacity and efficiency of the compressor limits the amount of compressed hydrogen.

Chapter 4

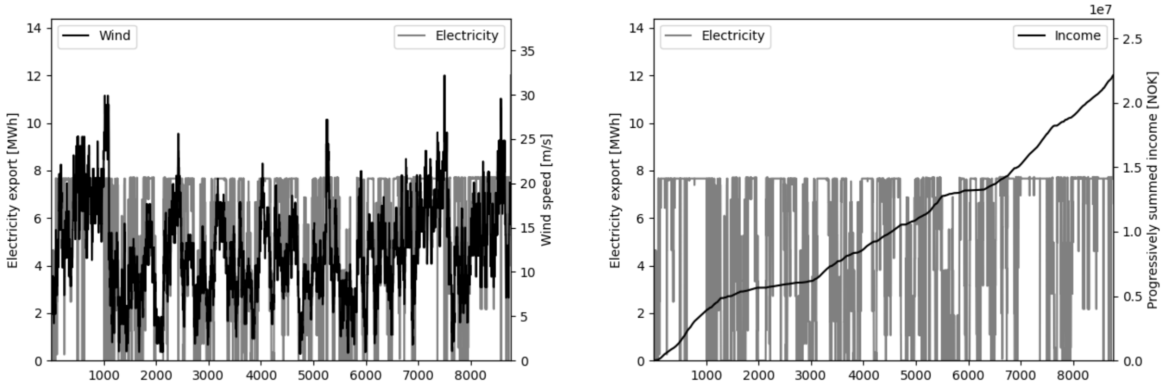
Benchmark, Results and Sensitivity Analysis

This chapter aims to provide the reader with results from the optimisation model in an understandable manner. Section 4.1 shows what the results of a benchmark test with a single turbine are with realistic costs and efficiencies equal to zero. Section 4.2 shows results from the optimisation model with realistic input parameters. This chapter will also calculate the net present value of revenue for different scenarios. Section 4.3 presents the sensitivity analysis where key parameters are varied to determine what the most important cost-driving factors are.

Unfortunately, the optimisation model is not working as intended. This was regrettably caught too close to the deadline and there was not enough time to come up with an adequate solution. There seems to be an issue with the storage part of the model, with hydrogen only being stored for a single time step, then exported the next time step. This will of course limit the model to not solve one of the primary objectives of the task, re-electrifying hydrogen for high electricity demand periods. It also means that storage and fuel cell costs are too low to give a representative result for a proper power-to-gas system. The model now operates as a continuous exporting hydrogen plant that would serve its purpose as a source of hydrogen for industrial purposes through pipelines, but not as previously stated. What might solve the problem would be to constrain how often hydrogen may be exported, forcing the model to store hydrogen if profitable or export electricity directly if that is more profitable. Nonetheless, the results will be discussed in the following sections and the possible differences will be explained.

4.1 Benchmark Test

To acquire a point of reference for the system, the optimisation is run with an electrolyser efficiency of zero. This forces the model to only export electricity as electrolysis is impossible.



(a) Electricity export and wind speed, benchmark

(b) Electricity export and income, benchmark

Figure 4.1: Results of benchmark

Figure 4.1a shows how electricity export varies with wind speed. As discussed previously, the wind speeds are to a large degree situated either in the rated region or below the cut-in speed of the chosen wind turbine. This results in the power output to mostly alternate between maximum output and no output. Subsequently, the income is relatively linear, albeit with two occurrences of extended periods of time with a lower rate of increase. These areas are between 1 200 - 3 000 hours and 5 500 - 6 500 hours. This is shown in Figure 4.1b. As shown in the aforementioned figure, the total income from the benchmark is approximately NOK 22.1 million. Since the cost of the turbine and its operational costs are considered outside the scope of this thesis, this value will serve as a baseline for further calculations. Profit above this value will be treated as an increase in profitability for the system, which is made apparent in the sensitivity analysis in Section 4.3.

The calculation of the net present value of the benchmark is shown in Equation 4.1 below.

$$NPV_{benchmark} = \sum_{t=0}^{T} \frac{NOK\ 22.1\, million}{(1+0.075)^t} = NOK\ 242.6\, million \tag{4.1}$$

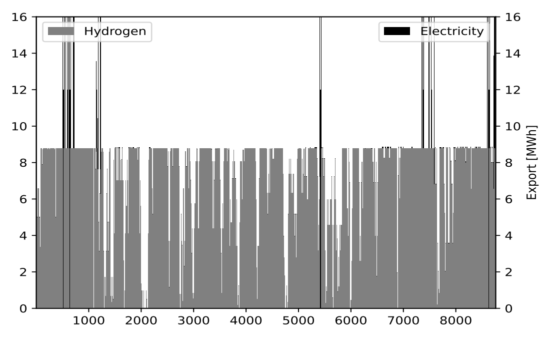
4.2 Realistic efficiencies, high capacity costs and low hydrogen price

Upon completion of the benchmark, it is time to test the model. In this scenario, realistic efficiencies and high costs are investigated. The scenario uses, as far as possible, the median values for efficiencies acquired earlier in this thesis. Costs of storage at 18 MPa is used and operational expenses are assumed to be 3% of their respective capacity costs, which are assumed to be at the high end of the spectrum. The capacity cost of compression is a fixed cost of 600 000/MW$_{H_2}$, which is the cost of compression from 1-18 MPa. The input parameters and their respective values are shown in Table 4.1. Hydrogen price is assumed to be in the lower end of the scale at around NOK 25/kg$_{H_2}$, translating to approximately NOK 750 /MWh$_{H_2}$. As mentioned earlier, the computer that ran the optimisation was unable to optimise for 20 years straight, but this was considered. Costs were scaled to reduce the impact of this obstacle, and the alterations are seen in *optimisationModelRevised.py* in Appendix A.

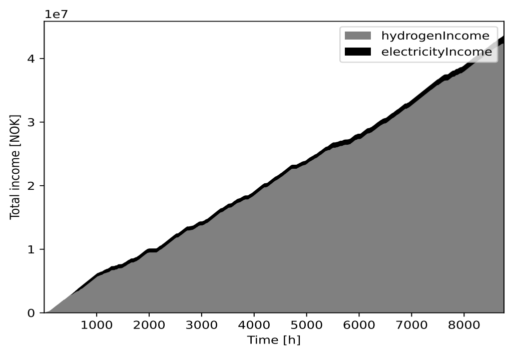
Table 4.1: Input parameters, scenario 1

Unit	Parameters			
$[-]$	$\eta_{ec} : 0.8$	$\eta_{fc} : 0.6$	$\eta_c : 0.915$	$\eta_{H2} : 1.0$
$[NOK1000]$	$C_c^{ec} : 11\,800$	$C_c^{fc} : 29\,350$	$C_c^c : 600$	$C_c^{H2} :\ 83.15$
$[NOK1000]$	$C_o^{ec} : 2\%C_c$	$C_o^{fc} : 2\%C_c$	$C_o^c : 2\%C_c$	$C_o^{H2} : 0$

Figure 4.2a shows the electricity and hydrogen export for this scenario. In this scenario, the optimisation model deems it not profitable to export electricity as the hydrogen prices are too high. As a result, the income of this scenario is substantially higher than the benchmark.



(a) Electricity and hydrogen export



(b) Electricity export and income

Figure 4.2: Results of optimisation

Figure 4.2a shows the time series of exported electricity and hydrogen in MWh. There are some areas where total production is above the capacity of the wind turbine, but this is due to the storage-part of the optimisation model that is not cooperating. Hydrogen is stored for an hour, then exported along with electricity, resulting the spikes. The total export is nonetheless not higher than the output of the turbine. As seen in the plot, the optimisation model has deemed almost pure hydrogen as the most profitable scenario, with electricity covering the excess power production.

Figure 4.2b shows the progressively summed income throughout one year. It is clearly seen that almost all export is in the form of hydrogen, while electricity covers peak performance. This results in a total income of approximately NOK 43 million, a power capacity for the electrolysers of 12 MW, storage capacity of 8.784 MWh and water consumption of 23 200 cubic meters.

The revenue of pure electricity export was as mentioned previously, approximately NOK 22.1 million, resulting in an NPV of NOK 242.6 million. In this scenario, the result of the optimisation is 32.1 million, yielding an NPV of NOK 351.2 million as shown in Equation 4.2.

$$NPV_{scenario\,1} = \sum_{t=0}^{T} \frac{NOK\ 32.1\,million}{(1+0.075)^t} = NOK\ 351.2\,million \tag{4.2}$$

To evaluate these results further, a sensitivity analysis will be performed in the following chapter.

4.3 Sensitivity Analysis

In this section, the most important parameters for the system will be analysed with the benchmark as a basis. As mentioned previously, the model is not working as intended, with the storage of hydrogen for re-electrification not behaving correctly. Nonetheless, it is still possible to find the cost-driving factors for a system that continuously exports hydrogen rather than storing it for long-term applications.

When analysing a system like this, the most important parameters are hydrogen price, the electrolyser's efficiency and its respective costs. The results of varying these parameters will be presented throughout this section. As presented earlier, the NPV of the benchmark was approximately NOK 242.6 million. Any results above this value will be considered an increase in value of the system.

4.3.1 Hydrogen Price Variation

In this analysis, hydrogen price is varied between NOK 500 and NOK 2 000 per MWh hydrogen, translating to approximately NOK 15 and NOK 60 per kg hydrogen, respectively. 500 was chosen as the lower limit as it is the minimum hydrogen price that results in an increase in profitability compared to only exporting electricity directly to the grid. 2 000 was chosen as the upper limit as it is above the maximum price of green hydrogen as stated in the background of this thesis. Figure 4.3 shows how the change in profitability varies depending on hydrogen selling price. The baseline is at the medium cost of hydrogen at NOK 1 250 per MWh$_{H_2}$ and values above this are treated as an increase in profitability.

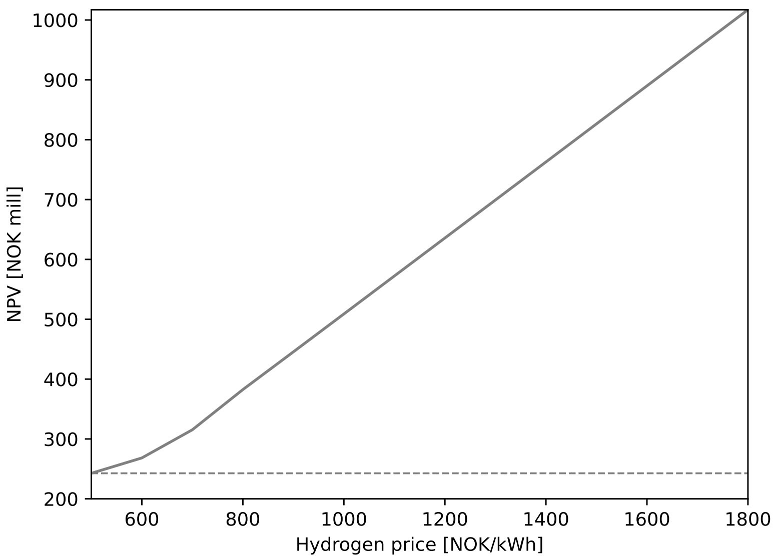


Figure 4.3: Sensitivity analysis 1: Hydrogen price variation

By studying the plot, it becomes apparent that variations in the hydrogen price affect the profitability of the system to a significant degree. The curve is almost completely linear except for prices between NOK 500-600. This is because the optimisation model quickly deems hydrogen export more profitable than electricity. A possible explanation to this is that the model is not working as intended, and costs subsequently are significantly lower than what they should be. As mentioned this has been handled to a certain degree, but from the results of the sensitivity analysis, it is clear that it needs more work. The baseline is illustrated with a dashed line showing what the NPV of a system only exporting electricity is.

4.3.2 Electrolyser Efficiency

In this section, the effect of varying the efficiency of the electrolyser will be analysed. Although PEM electrolysers have come quite far engineering wise, there is some room for improvements. In this thesis, the efficiency of the electrolysers has been set to 80% in line with relevant literature. As mentioned in the background of this chapter, the theoretical limit for electric efficiency for electrolysers is approximately 94%. Since it is highly unlikely of achieving efficiencies of 94%, 90% will serve as the upper limit for this analysis. The lower limit is set to 50% as this is the point where the optimisation model will choose pure electricity export rather than hydrogen. Using this analysis, is has been made clear that a system like this has a higher value than pure electricity export if the efficiency of the electrolysers are above 55%.

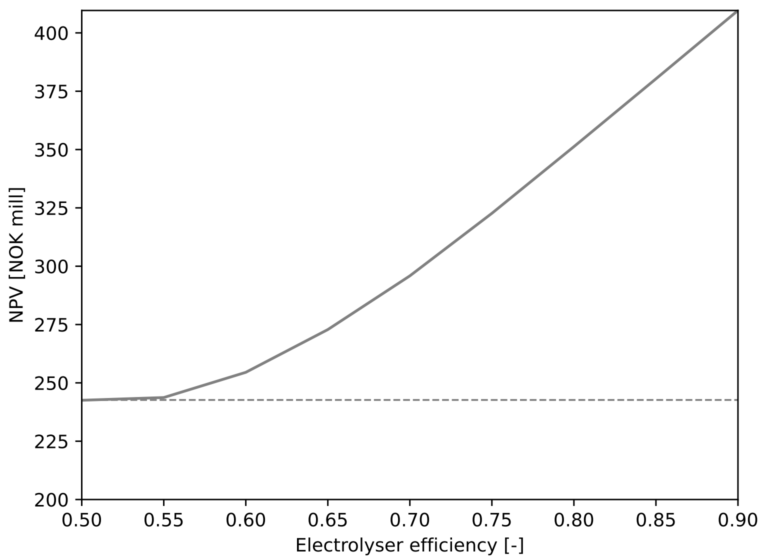


Figure 4.4: Sensitivity analysis 2: Electrolyser efficiency variation

As seen in Figure 4.4, the NPV of the system increases drastically with positive changes in electrolyser efficiency. For every 5% increase in efficiency, the NPV increases somewhere between 8-9%. This analysis also proves how important efficiency is and why electrolysers have been researched for decades and most likely will in the future also.

4.3.3 Electrolyser Capacity Cost Variation

The last parameter to be investigated is the electrolyser capacity cost. As stated in the background of this thesis, PEMEC capacity cost is between NOK 7 000 - 11 800 per kW as of 2020, but is expected to have a decrease to somewhere between NOK 2 100 - 3 800 per kW by 2050. This equivalent to a decrease of about 70% from today's cost.

Figure 4.5 below shows how the NPV changes with varying electrolyser capacity cost. In this analysis, the lower value for capacity costs is set to NOK 10 000 and the higher value to NOK 30 000. The lower value was chosen at it is approximately in the middle of today's upper and lower value. This indicates that economies of scale have taken effect to lower the cost from the upper level. The upper limit is defined as the capacity cost where the model chooses to export electricity instead.

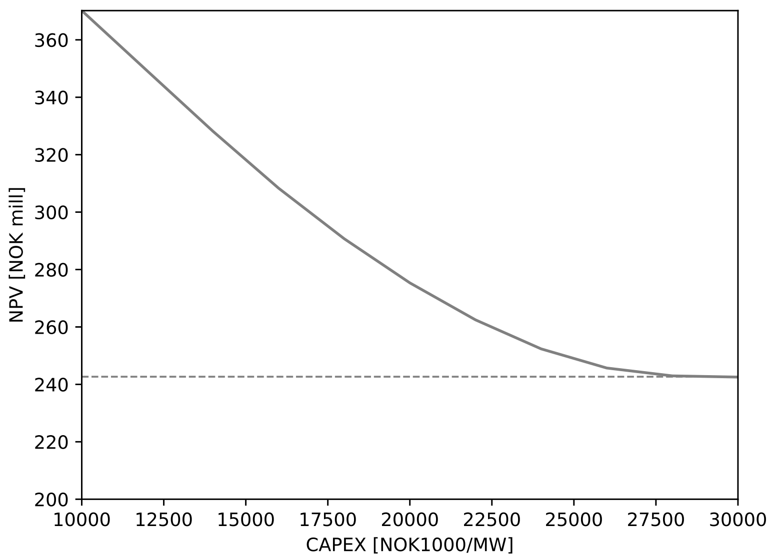


Figure 4.5: Sensitivity analysis 3: Electrolyser capacity cost variation

Figure 4.5 shows a significant decrease in NPV when costs are increased from NOK 10 000. Although it might be interesting to see how much the NPV can increase by decreasing capacity costs to levels for 2030, 2040 or 2050, the focus was on the highest possible cost that still resulted in hydrogen production. From the plot, is becomes apparent that as long as capacity costs are below NOK 28 000, the system will prefer to export a combination of electricity and hydrogen.

For a frame of reference, the NPV for the lower capacity costs of 2030, 2040 and 2050 are included as well in Table 4.2.

Table 4.2: Projected capacity costs effect on NPV

Year	2030	2040	2050
NPV	NOK 435.4 million	NOK 449.6 million	NOK 453.3 million

Table 4.2 shows that NPV will increase significantly from today's values by 2030, but that the increase will slow down from 2030 towards 2050. The increase from today's NPV is approximately 24.0%, 28.0% and 29.0% for 2030, 2040 and 2050, respectively.

4.3.4 Operational Expenditure Variation

In this section, the OPEX of the system is analysed. As mentioned in the background of this thesis, the operational expenditure is usually in the range of 1-3% of the capacity costs per year. Figure 4.6 shows the relationship between operational costs and the NPV of the system.

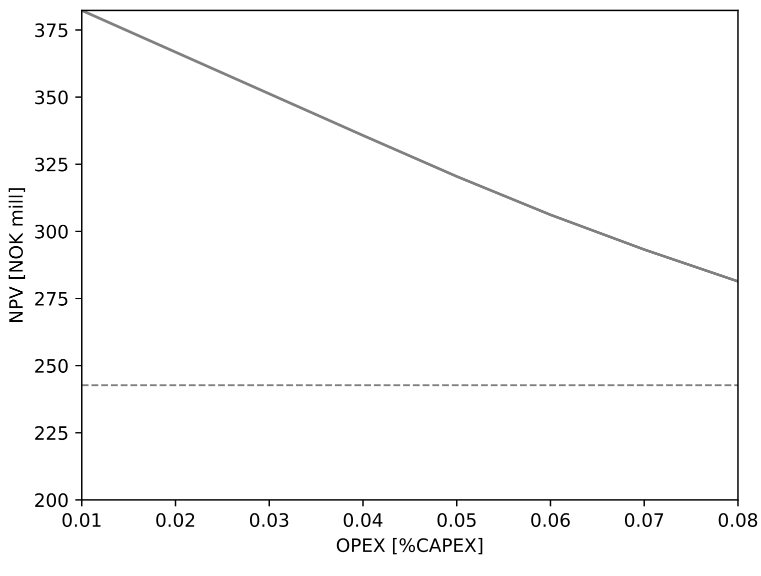


Figure 4.6: Sensitivity analysis 4: Operational expenditure variation

As seen in Figure 4.6, even though the operational costs are increased by three times its starting value, the model still determines that hydrogen production is beneficial. The decrease in NPV from 1% OPEX to 8% OPEX is only 26.4% even though the operational costs have octupled.

4.4 Discussion

The primary objective in this thesis was to determine under what conditions offshore wind-powered hydrogen production is economically viable. During the course of this thesis, the model has shown that it is unable to provide the full picture, as storage costs are not handled correctly. Several challenges have occurred throughout writing this thesis, with the storage section of the optimisation model and the shear computational power needed, proving to be the most challenging. As stated earlier, the problem was caught too close to the deadline. Subsequently, the results are more valid for a continuous exporting hydrogen plant rather than how it was initially intended. A potential solution to the problem with the model is to constrain the model to only export hydrogen at certain points in time, simulating ship export. This would force the model to either store hydrogen or export pure electricity if this would be more profitable. Whether this will increase or decrease the profitability

Nonetheless, the model provides valuable information about the production of hydrogen and could serve as a model for optimising direct hydrogen export plants. The study demonstrates a clear correlation between efficiencies, costs and hydrogen prices. The thesis also demonstrates that some parameters are more critical for a profitable green hydrogen production plant than others.

As mentioned, the correlation between input parameters and profitability of the system has been made clear through various analyses in this thesis. It should be noted that the initial objective was based on utilising low electricity demand periods to produce economically competitive. Electricity price variations will therefore not provide an accurate representation of how a fully functional power-to-gas system's profitability alters. The model created in this thesis will instead choose to export hydrogen if electricity prices are too low, minimising the impact of low electricity prices. Based on the findings in the sensitivity analysis, the net present value of the system is more dependent on some parameters than others. Electrolyser efficiency and hydrogen cost have proven to have a significant impact on a system like this, while operational costs have shown to affect the system less. Although these results give a clear indication for this specific model, it is highly likely that the results are different from a model that stores hydrogen properly as more parameters come into play.

Hydrogen price has shown itself as a crucial parameter of the model's profitability, as one might expect. The sensitivity analysis quickly turns linear, with a high rate of increase in NPV. This is a result of the model deeming pure hydrogen production to be the most profitable relatively early on in the analysis. For the scenario that was analysed, hydrogen production is not economically viable at hydrogen prices lower than NOK 500 /kWh$_{H_2}$. Hydrogen cost from renewable sources generally lies between NOK 750 - 1 950 /kW$_{H_2}$ while hydrogen cost from natural gas typically is from NOK 750 per kWh$_{H_2}$ and down. In conclusion, the system is able to produce profitable hydrogen at prices below the maximum price of grey hydrogen, but should preferably export at higher costs to achieve a larger profit margin. Due to economies of scale, learning curves and assuming that efficiencies remain at pessimistic levels, it should be possible to produce even more competitive hydrogen in the years to come, even with decrease in end-user costs.

Electrolyser efficiency also plays a crucial role in the profitability of this system. The profitability translates relatively linearly with positive electrolyser efficiency variation with a slight exponential tendency at the start. If the electrolyser efficiency approaches its theoretical maximum, the profitability of the system increases by more than 60% and the hydrogen production becomes unprofitable when the efficiency approaches 55%.

The last analysed parameter was the capacity cost of the electrolyser. Capacity cost is an area with great potential for improvements. As stated in the background of this thesis, the costs are expected to decrease from NOK 7 000 - 11 800 per kW to about NOK 2 100 - 3 500 per kW by 2050. This significant decrease in cost will play a crucial part in making green hydrogen a reality. As seen in the sensitivity analysis, profitability growth is expected with decreased costs of electrolysers, but the increase will slow down after 2030.

Another important factor in this thesis is the modelling of wind speeds and electricity prices. As mentioned previously, Markov chains are inherently incapable of predicting seasonality. This has been handled to a certain degree by simulating each month individually, but another forecasting method, e.g. *autoregressive integrated moving average* or *quantile regression*, could be a more fitting option. A comparative study of different forecasting methods was considered outside the scope of this thesis as was therefore not investigated. Nonetheless, it would be interesting to see the outcome of using a multitude of predictions models and how it would affect the end-result.

Chapter 5

Conclusion and Further Work

The following chapter provides concluding remarks based on the results from the former chapter. In addition to a conclusion, possible ways of improving or building upon the model created for this thesis and how it can be used to solve other problems will also be discussed.

5.1 Conclusion

The objective of this thesis was to determine under what conditions offshore hydrogen production is economically viable. Although the approach to this problem statement has evolved during the writing of this thesis, the results have still proven significant value and insight into how and when a system like this will be profitable.

Although Markov chains do not predict seasonality, the manual seasonality handling made the simulation results more applicable. The predicted data for both spotprices and wind speeds seems representative for an analysis like this without an in-depth analysis of prediction models.

Of the optimisation parameters that were investigated, some have proven more crucial than others. Granting, the profitability of an offshore wind-powered hydrogen plant is dependent on the combination of input parameters, there are some that affect the system more than others. Hydrogen price and efficiencies of electrolysers have proven to be the most likely to affect the profitability the most. Even though it is predicted that green hydrogen will sell for less in the future, efficiencies have been steadily increasing over the years and is likely to help keeping profits high. This will prove crucial in producing zero/low-emission hydrogen to supply a growing population and energy demand.

Low-emission hydrogen prices are expected to decrease in the future as carbon capture matures and costs decrease. For green hydrogen to be a viable option to carbon-based alternatives, we must overcome several technical obstacles and components have to be take advantage of economies of scale to reduce production costs. Both of these challenges are currently being worked on and all that is needed is a catalyst to grow this industry.

This thesis provides valuable insight into green hydrogen production. From the inner workings of different fuel cell technologies, through market trends, time-series forecasting and optimisation, this thesis should form a solid foundation for further work with green hydrogen production.

5.2 Further Work

An obvious way forward would be to determine what prohibits the model from storing hydrogen for long-term purposes. Most likely this is due to a complication with the constraints, and a limitation on when export of hydrogen is allowed, could be a possible solution. When this is handled, the model should provide a more in-depth picture of the system and volatility of electricity prices can finally be utilised to its full potential. It should also be noted that this optimisation model should be run on a powerful computer to be able to optimise for the whole lifetime of the fuel cells and electrolysers.

Subsequent to solving the storage problem, a potential next step could be to do a full analysis on different storage solutions, both how they affect the profitability of the system but also how it affects transportation and end-user costs. Apart from the traditional storage methods, salt caverns and empty oil reservoirs could potentially provide enormous storing potential with low compression costs.

To reduce capacity costs of fuel cells and electrolysers, reversible fuel cells should be investigated. SOFCs and PEMFCs have the potential to work as reversible cells, subsequently reducing the investment costs and freeing more space for other components. If this is to be done, one would have to determine if fuel cell capacity and electrolyser capacity are similar enough to warrant a system like this. This is because the capacity would be the same for fuel cells and electrolysers when using reversible cells, albeit with variations in efficiencies.

As already known, PEMECs can achieve relatively high output pressures. It is more energy-efficient to increase pressure within the cell than externally. Knowing this, using high pressure electrolysers could potentially reduce compression costs as output pressures can be high enough for large scale storage. If possible, a combination of reversible- and high output fuel cells could potentially reduce costs of power-to-gas systems drastically.

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Appendix A

Code

The most important code is included in in this appendix for whom might find it useful to eliminate the need of a complete re-engineering of the model and its inputs. Although all figures in this thesis are made using Python, their code will not be included in this delivery because the of the number of pages it would add and their relevance for the end result is minimal. The files that are not included should not be a great hindrance for anyone wanting to recreate the model or develop it further. The codes that are included are the optimisation model, the input file containing all relevant parameters and an in-depth explanation to the *average day* plot shown in the background of this thesis.

A Python

A.1 optimisationModel.py

```python
"""
Author: Benjamin Madsen
Master's thesis - Spring 2021
Updated: 09/06/21
"""
import numpy as np
import pandas as pd
from gurobipy import *
from optimisationInput import*

nYears = 20

# Time range
T = np.arange(0, 8760 * nYears, 1)
Tno1 = np.arange(1, 8760 * nYears, 1)

Year = '2050'
scaleCost = 'low'
scaleEfficiency = 'med'
hydrogenCost = 'low'

if hydrogenCost == 'low':
    CH2 = cH2low
elif hydrogenCost == 'med':
    CH2 = cH2med
elif hydrogenCost == 'high':
    CH2 = cH2hi
else:
    CH2 = 0
```

```python
if scaleEfficiency == 'low':
    eta_ec  = etaEC_low
    eta_fc  = etaFC_low
    eta_c   = etaC18_med
elif scaleEfficiency == 'med':
    eta_ec  = etaEC_med
    eta_fc  = etaFC_med
    eta_c   = etaC18_med
else:
    eta_ec  = etaEC_hi
    eta_fc  = etaFC_hi
    eta_c   = etaC18_med

if Year == '2020':
    if scaleCost == 'low':
        CC_ec   = eCap20low
        CC_fc   = fcCap20low
    else:
        CC_ec   = eCap20hi
        CC_fc   = fcCap20hi
elif Year == '2030':
    if scaleCost == 'low':
        CC_ec   = eCap30low
        CC_fc   = fcCap30low
    else:
        CC_ec   = eCap30hi
        CC_fc   = fcCap30hi
elif Year == '2040':
    if scaleCost == 'low':
        CC_ec   = eCap40low
        CC_fc   = fcCap40low
    else:
```

```
        CC_ec    = eCap40hi
        CC_fc    = fcCap40hi
else:
    if scaleCost == 'low':
        CC_ec = eCap50low
        CC_fc = fcCap50hi
    else:
        CC_ec = eCap50hi
        CC_fc = fcCap50hi


# Parameters

newListSpotprice = listSpotprice*nYears
newListPowerProduction = listPowerProduction*nYears
Ce       = np.array(newListSpotprice)[T.astype(int)]
Ae       = np.array(newListPowerProduction)[T.astype(int)]
CC_c     = cCap18
CC_H2    = sCapPresLow
OC_ec    = 0.03 * CC_ec
OC_fc    = 0.03 * CC_fc
OC_c     = 0.03 * CC_c
OC_H2    = 0.00 * CC_H2
Pc       = Pc20

# Model
m = Model()

# Decision variables
xex          = m.addVars(T, vtype=GRB.CONTINUOUS, name="xex")
xrH2         = m.addVars(T, vtype=GRB.CONTINUOUS, name="xrH2")
xec          = m.addVars(T, vtype=GRB.CONTINUOUS, name="xec")
xH2x         = m.addVars(T, vtype=GRB.CONTINUOUS, name="xH2x")
```

```
vH2          = m.addVars(T, vtype=GRB.CONTINUOUS, name="vH2")
pH2          = m.addVar(vtype=GRB.CONTINUOUS, name="pH2")
pfc          = m.addVar(vtype=GRB.CONTINUOUS, name="pfc")
pec          = m.addVar(vtype=GRB.CONTINUOUS, name="pec")
pc           = m.addVar(vtype=GRB.CONTINUOUS, name="pc")
delta_ec     = m.addVars(T, vtype=GRB.BINARY, name="delta_ec")
delta_fc     = m.addVars(T, vtype=GRB.BINARY, name="delta_fc")

Pfcmin = 0.1 * pfc
Pecmin = 0.1 * pec

# Big number M
M = GRB.INFINITY

# Update model with decision variables
m.update()

# Define and set objective function
powerExport          = sum(Ce[t] * (xex[t] + xrH2[t]) for t in T)
hydrogenExport       = sum(CH2 * xH2x[t] for t in T)
storageCost          = pH2 * (CC_H2 + ((1/8760) * sum(OC_H2 for t in T)))
fuelcellCost         = pfc * (CC_fc + ((1/8760) * sum(OC_fc for t in T)))
electrolysisCost     = pec * (CC_ec + ((1/8760) * sum(OC_ec for t in T)))
compressorCost       = (pc * CC_c) + (sum(Ce[t] * Pc * (vH2[t] - vH2[t-1]) for t
↪   in Tno1))
waterCost            = sum(cW * xW * xec[t] * eta_ec for t in T)
objectiveFunction    = powerExport + hydrogenExport - storageCost - fuelcellCost
↪   - electrolysisCost - waterCost
m.setObjective(objectiveFunction, GRB.MAXIMIZE)


# Constraints
c1 = m.addConstrs(xex[t] + xec[t] <= Ae[t] for t in T)
```

```
# c1: Sum of exported electricity and power consumption of electrolysers is
↪ limited by available power
c2 = m.addConstrs(xec[t] <= pec for t in T)
# c2: Electrolyser consumption is limited by capacity of electrolysers
c3 = m.addConstrs(xec[t] <= (M * (1 - delta_ec[t])) for t in T)
#  c3: Electricity is not exported if electrolyser is active
c4 = m.addConstrs(Pecmin - xec[t] <= (M * delta_ec[t]) for t in T)
# c4: Electrolyser consumption must be higher than the minimum operation
↪ capacity or be off
c5 = m.addConstrs(xrH2[t] <= eta_fc * pfc for t in T)
# c5: Re-electrified hydrogen is limited by efficiency and capacity of fuel cell
c6 = m.addConstrs(xrH2[t] <= M * (1 - delta_fc[t]) for t in T)
# c6: Hydrogen is not re-electrified if fuel cell is inactive
c7 = m.addConstrs(Pfcmin - xrH2[t] <= M * delta_fc[t] for t in T)
# c7: Re-electrification is limited to values between min operating capacity and
↪ fuel cell being active
c8 = m.addConstrs(xrH2[t] >= Pfcmin for t in T)
# c8: Re-electrification is limited by minimum operation capacity of fuel cell
c9 = m.addConstrs(vH2[t-1] + (xec[t-1] * eta_ec * eta_c) - (xrH2[t-1]/eta_fc) -
↪ xH2x[t-1] == vH2[t] for t in Tno1)
# c9: Storage level at (t-1) + electrolysed and compressed hydrogen at (t-1) -
↪ re-electrified hydrogen at (t-1) - exported hydrogen at (t-1) = storage
↪ level at t
c10 = m.addConstrs(vH2[t] <= pH2 for t in T)
# c10: Storage level at t is less or equal to power capacity of storage
c11 = m.addConstrs((xrH2[t]/eta_fc) + xH2x[t] <= vH2[t] for t in T)
# c11: Re-electrified hydrogen + hydrogen export at t is less or equal to
↪ storage level at t
c12 = m.addConstrs(xex[t] >= 0 for t in T)
# c12: Non-negativity constraint
c13 = m.addConstrs(xrH2[t] >= 0 for t in T)
# c13: Non-negativity constraint
c14 = m.addConstrs(xec[t] >= 0 for t in T)
```

```
# c14: Non-negativity constraint
c15 = m.addConstrs(vH2[t] >= 0 for t in T)
# c15: Non-negativity constraint
c16 = m.addConstrs(pec >= 0 for t in T)
# c16: Non-negativity constraint
c17 = m.addConstrs(pfc >= 0 for t in T)
# c17: Non-negativity constraint
c18 = m.addConstrs(pH2 >= 0 for t in T)
# c18: Non-negativity constraint
c19 = m.addConstrs(pc >= 0 for t in T)
# c19: Non-negativity constraint
c20 = m.addConstrs(vH2[t] - vH2[t-1] <= eta_c * pc for t in Tno1)
# c20: Amount of compressed hydrogen at time t can not be more than the capacity
↪  of compressor and its efficiency


# Run optimisation
m.optimize()
```

A.2 optimisationModelRevised.py

```
"""
Author: Benjamin Madsen
Master's thesis - Spring 2021
Updated: 09/06/21
"""
import numpy as np
import pandas as pd
from gurobipy import *
from optimisationInput import*

nYears = 1

# Time range
T = np.arange(0, 8760 * nYears, 1)
Tno1 = np.arange(1, 8760 * nYears, 1)

Year = '2050'
scaleCost = 'low'
scaleEfficiency = 'med'
hydrogenCost = 'low'

if hydrogenCost == 'low':
    CH2 = cH2low
elif hydrogenCost == 'med':
    CH2 = cH2med
elif hydrogenCost == 'high':
    CH2 = cH2hi
else:
    CH2 = 0

if scaleEfficiency == 'low':
    eta_ec  = etaEC_low
```

```python
    eta_fc  = etaFC_low
    eta_c   = etaC18_med
elif scaleEfficiency == 'med':
    eta_ec  = etaEC_med
    eta_fc  = etaFC_med
    eta_c   = etaC18_med
else:
    eta_ec  = etaEC_hi
    eta_fc  = etaFC_hi
    eta_c   = etaC18_med

if Year == '2020':
    if scaleCost == 'low':
        CC_ec   = eCap20low
        CC_fc   = fcCap20low
    else:
        CC_ec   = eCap20hi
        CC_fc   = fcCap20hi
elif Year == '2030':
    if scaleCost == 'low':
        CC_ec   = eCap30low
        CC_fc   = fcCap30low
    else:
        CC_ec   = eCap30hi
        CC_fc   = fcCap30hi
elif Year == '2040':
    if scaleCost == 'low':
        CC_ec   = eCap40low
        CC_fc   = fcCap40low
    else:
        CC_ec   = eCap40hi
        CC_fc   = fcCap40hi
else:
```

```python
    if scaleCost == 'low':
        CC_ec = eCap50low
        CC_fc = fcCap50hi
    else:
        CC_ec = eCap50hi
        CC_fc = fcCap50hi



# Parameters


newListSpotprice = listSpotprice*nYears
newListPowerProduction = listPowerProduction*nYears
Ce       = np.array(newListSpotprice)[T.astype(int)]
#Ce       = np.array(listSpotprice)[T.astype(int)]
#Ae       = np.array(listPowerProduction)[T.astype(int)]
Ae       = np.array(newListPowerProduction)[T.astype(int)]
CC_c     = cCap18
CC_H2    = sCapPresLow
OC_ec    = 0.03 * CC_ec
OC_fc    = 0.03 * CC_fc
OC_c     = 0.03 * CC_c
OC_H2    = 0.00 * CC_H2
Pc       = Pc20

# Model
m = Model()

# Decision variables
xex          = m.addVars(T, vtype=GRB.CONTINUOUS, name="xex")
xrH2         = m.addVars(T, vtype=GRB.CONTINUOUS, name="xrH2")
xec          = m.addVars(T, vtype=GRB.CONTINUOUS, name="xec")
xH2x         = m.addVars(T, vtype=GRB.CONTINUOUS, name="xH2x")
vH2          = m.addVars(T, vtype=GRB.CONTINUOUS, name="vH2")
```

```
pH2          = m.addVar(vtype=GRB.CONTINUOUS, name="pH2")
pfc          = m.addVar(vtype=GRB.CONTINUOUS, name="pfc")
pec          = m.addVar(vtype=GRB.CONTINUOUS, name="pec")
pc           = m.addVar(vtype=GRB.CONTINUOUS, name="pc")
delta_ec     = m.addVars(T, vtype=GRB.BINARY, name="delta_ec")
delta_fc     = m.addVars(T, vtype=GRB.BINARY, name="delta_fc")

Pfcmin = 0.1 * pfc
Pecmin = 0.1 * pec

# Big number M
M = GRB.INFINITY

# Update model with decision variables
m.update()

# Define and set objective function
powerExport         = sum(Ce[t] * (xex[t] + xrH2[t]) for t in T)
hydrogenExport      = sum(CH2 * xH2x[t] for t in T)
storageCost         = pH2 * (CC_H2 + ((20/8760) * sum(OC_H2 for t in T)))
fuelcellCost        = pfc * (CC_fc + ((20/8760) * sum(OC_fc for t in T)))
electrolysisCost    = pec * (CC_ec + ((20/8760) * sum(OC_ec for t in T)))
compressorCost      = (pc * CC_c) + (sum(Ce[t] * Pc * (vH2[t] - vH2[t-1]) for t
↪   in Tno1))
waterCost           = sum(cW * xW * xec[t] * eta_ec for t in T)
objectiveFunction   = powerExport + hydrogenExport - storageCost - fuelcellCost
↪   - electrolysisCost - waterCost
m.setObjective(objectiveFunction, GRB.MAXIMIZE)


# Constraints
c1 = m.addConstrs(xex[t] + xec[t] <= Ae[t] for t in T)
```

```
# c1: Sum of exported electricity and power consumption of electrolysers is
↪  limited by available power
c2 = m.addConstrs(xec[t] <= pec for t in T)
# c2: Electrolyser consumption is limited by capacity of electrolysers
c3 = m.addConstrs(xec[t] <= (M * (1 - delta_ec[t])) for t in T)
#  c3: Electricity is not exported if electrolyser is active
c4 = m.addConstrs(Pecmin - xec[t] <= (M * delta_ec[t]) for t in T)
# c4: Electrolyser consumption must be higher than the minimum operation
↪  capacity or be off
c5 = m.addConstrs(xrH2[t] <= eta_fc * pfc for t in T)
# c5: Re-electrified hydrogen is limited by efficiency and capacity of fuel cell
c6 = m.addConstrs(xrH2[t] <= M * (1 - delta_fc[t]) for t in T)
# c6: Hydrogen is not re-electrified if fuel cell is inactive
c7 = m.addConstrs(Pfcmin - xrH2[t] <= M * delta_fc[t] for t in T)
# c7: Re-electrification is limited to values between min operating capacity and
↪  fuel cell being active
c8 = m.addConstrs(xrH2[t] >= Pfcmin for t in T)
# c8: Re-electrification is limited by minimum operation capacity of fuel cell
c9 = m.addConstrs(vH2[t-1] + (xec[t-1] * eta_ec * eta_c) - (xrH2[t-1]/eta_fc) -
↪  xH2x[t-1] == vH2[t] for t in Tno1)
# c9: Storage level at (t-1) + electrolysed and compressed hydrogen at (t-1) -
↪  re-electrified hydrogen at (t-1) - exported hydrogen at (t-1) = storage
↪  level at t
c10 = m.addConstrs(vH2[t] <= pH2 for t in T)
# c10: Storage level at t is less or equal to power capacity of storage
c11 = m.addConstrs((xrH2[t]/eta_fc) + xH2x[t] <= vH2[t] for t in T)
# c11: Re-electrified hydrogen + hydrogen export at t is less or equal to
↪  storage level at t
c12 = m.addConstrs(xex[t] >= 0 for t in T)
# c12: Non-negativity constraint
c13 = m.addConstrs(xrH2[t] >= 0 for t in T)
# c13: Non-negativity constraint
c14 = m.addConstrs(xec[t] >= 0 for t in T)
```

```
# c14: Non-negativity constraint
c15 = m.addConstrs(vH2[t] >= 0 for t in T)
# c15: Non-negativity constraint
c16 = m.addConstrs(pec >= 0 for t in T)
# c16: Non-negativity constraint
c17 = m.addConstrs(pfc >= 0 for t in T)
# c17: Non-negativity constraint
c18 = m.addConstrs(pH2 >= 0 for t in T)
# c18: Non-negativity constraint
c19 = m.addConstrs(pc >= 0 for t in T)
# c19: Non-negativity constraint
c20 = m.addConstrs(vH2[t] - vH2[t-1] <= eta_c * pc for t in Tno1)
# c20: Amount of compressed hydrogen at time t can not be more than the capacity
↪ of compressor and its efficiency


# Run optimisation
m.optimize()
```

A.3 optimisationInput.py

```
"""
Author: Benjamin Madsen
Master's thesis - Spring 2021
Updated: 09/06/21
"""

import pandas as pd
import numpy as np

# Wind speed data
windFile = open(r'C:\Users\benja\OneDrive - NTNU\S2021\Master
↪  Thesis\Code\Matlab\windSpeedSim.csv')
dfWind = pd.read_csv(windFile, header=None, skiprows=1)
dfWind.columns = ['Wind speed [m/s]']
dfWind.insert(0, 't', np.arange(1, 8761, 1))
listWind = dfWind['Wind speed [m/s]'].values.tolist()



# Electricity price data
spotpriceFile = open(r'C:\Users\benja\OneDrive - NTNU\S2021\Master
↪  Thesis\Code\Matlab\spotpriceSim.csv')
dfSpotprice = pd.read_csv(spotpriceFile, header=None, skiprows=1)
dfSpotprice.columns = ['Electricity price [NOK/MWh]']
listSpotprice = dfSpotprice['Electricity price [NOK/MWh]'].values.tolist()

# Hydrogen price data
cH2low  = 750  # NOK/MWh
cH2med  = 1250
cH2hi   = 1750

# Power production data
powerProductionFile = open(r'output\powerProduction\powerProductionSim.csv')
```

```
dfPowerProduction = pd.read_csv(powerProductionFile, header=None, skiprows=1)
dfPowerProduction.columns = ['t', 'Power output [MWh]']
dfPowerProduction['t'] = np.arange(1, 8761, 1)
dfPowerProduction['Power output [MWh]'] = dfPowerProduction['Power output
↪  [MWh]'].div(1000)
listPowerProduction = dfPowerProduction['Power output [MWh]'].values.tolist()



# Power demand data
powerDemandFile = open('input/spotpriceData/powerDemand.csv')
dfPowerDemand = pd.read_csv(powerDemandFile, header=None, skiprows=2)
dfPowerDemand['powerDemand'] = dfPowerDemand[7]
listPowerDemand = dfPowerDemand['powerDemand'].values.tolist()



# Hydrogen price data
dataPH2 = {'t': np.arange(1, 8761, 1), 'Price [NOK/MWh]': np.arange(1, 8761, 1)}
dfH2 = pd.DataFrame(dataPH2)
dfH2['Price [NOK/MWh]'] = 1000
listH2 = dfH2['Price [NOK/MWh]'].values.tolist()

# Electrolysis cells
eCap20low   = (7000 * 1000)/20  # [NOK/kW] -> [NOK/MW]
eCap20hi    = (11800 * 1000)/20
eCap30low   = (3800 * 1000)/20
eCap30hi    = (6500 * 1000)/20
eCap40low   = (2450 * 1000)/20
eCap40hi    = (4150 * 1000)/20
eCap50low   = (2100 * 1000)/20
eCap50hi    = (3500 * 1000)/20
etaEC_low   = 0.6
etaEC_med   = 0.8
etaEC_hi    = 0.94
```

```
# Fuel cells
fcCap15low  = (24900 * 1000)/20  # [NOK/kW] -> [NOK/MW]
fcCap15hi   = (33200 * 1000)/20
fcCap20low  = (22000 * 1000)/20
fcCap20hi   = (29350 * 1000)/20
fcCap30low  = (16200 * 1000)/20
fcCap30hi   = (21600 * 1000)/20
fcCap40low  = (10400 * 1000)/20
fcCap40hi   = (13850 * 1000)/20
fcCap50low  = (4600 * 1000)/20
fcCap50hi   = (6100 * 1000)/20
etaFC_low   = 0.5
etaFC_med   = 0.6
etaFC_hi    = 0.83
etaFCSens   = np.arange(0.1, 2.1, 0.1)*etaFC_med
# print("Sensitivity analysis electrolysis cell:" + str(etaFCSens))

# Compressors
cCap18      = (600 * 1000)/20  # [NOK/kWH2] -> [NOK/MWH2]
cCap70low   = (1650 * 1000)/20
cCap70hi    = (3300 * 1000)/20
etaC18_low  = 0.88
etaC18_med  = 0.915
etaC18_hi   = 0.95
etaC70_low  = 0.8
etaC70_med  = 0.855
etaC70_hi   = 0.91
Pc20        = 0.086  # [MWh_el/MWh_H2]
Pc35        = 0.102
Pc70        = 0.124
```

```
# Liquefiers
liqCapLow   = 7500
liqCapHi    = 16650
etaLiq      = 0.7

# Storage
sCapPresLow = (49900)/20  # [NOK/MWh]
sCapPresHi  = (83150)/20
sCapLiqLow  = (6650)/20
sCapLiqHi   = (83150)/20



# High pressure electrolyser
↪  https://www.energy.gov/sites/prod/files/2014/08/f18/fcto_2014_electrolytic_h2_wkshp_colel
eCapHipres  = 7820 * 1000
etaECHiPres = 0.61
cCap0       = 0
etaC0       = 1

# Water
cW = 15  # cost 1.5 dollar per kL -> 15 kr/kL ->
xW = 0.3  # usage 10 L/kg -> 0.3 L/kWh -> 0.3 kL/kWh
```

A.4 spotpriceVisualisationRaw.py

```
from matplotlib import pyplot as plt
import pandas as pd
import numpy as np



# Import csv and create dataframe
file = open('input/spotpriceData/spotprices.csv')
df = pd.read_csv(file)
format = '%d/%m/%Y %H:%M'
df['Time'] = pd.to_datetime(df['Time'], format=format)
df = df.set_index(pd.DatetimeIndex(df['Time']))
del df['Time']

# Group data by month and then time to calculate "average day"
df = df.groupby(by=[df.index.month, df.index.time])
df = df.aggregate({'Price':np.mean})

# Plot graph
x = np.arange(1,289, 1)
y = df['Price']
fig, ax = plt.subplots()
ax.plot(x,y)
ax.xaxis.set_label_text('')
ax.yaxis.set_label_text('Daily averages for each month [NOK/MWh]')
positions = np.arange(1, 266, 24)
labels =
↪  ('Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec')
plt.xticks(positions,labels)
plt.show()
```