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Investment in flexible hydrogen production from local wind power: Optimising timing, capacity and plant operations of an investment under uncertainty

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Problem description

This thesis considers a profit-maximising firm that holds the option to invest in large-scale hydrogen production from electrolysis. The production is assumed to be flexible and the cost of operation is mainly determined by the electricity price. The company has access to power from a local wind farm and must decide how to optimally use the available power to operate the hydrogen plant. In order to find the optimal timing and capacity of the investment under uncertainty a real options approach is applied.

Preface

This thesis has been written as the concluding part of our Master's degree programme at the Norwegian University of Science and Technology (NTNU). Our programme of study is Industrial Economics and Technology Management with a specialisation in Financial Engineering.

The thesis has been a unique opportunity to further develop our skills in both the fields of finance and technology. The result of our work provides financial insight towards the viability of producing hydrogen from renewable energy.

We would like to thank our supervisor, Associate Professor Verena Hagspiel, for valuable discussions, feedback and thorough guidance. We have taken great lessons from her knowledge into the field of real options and she has been a inspirational source throughout the work with the thesis. We would also like to thank the Head of Development at TrønderEnergi, Bernhard Kvaal, for giving us the opportunity to cooperate with TrønderEnergi and for useful discussions and relevant data. Further, we thank Steffen-Møller Holst and Anders Ødegård at SINTEF for providing valuable insights into the field of hydrogen economy and guidance towards model assumptions. We are also grateful for the extended guidance and advice towards electricity price modeling provided by Gunnar Aronsen, senior power analyst at TrønderEnergi. Lastly, we would like to thank NEL Hydrogen, Hexagon, Yara Praxair and AGA for providing input parameters to our model.

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Abstract

Hydrogen produced from renewable energy can be used as a zero emission fuel. While hydrogen has applications across several industries, its largest potential is seen as a fuel for hydrogen vehicles. Widespread adoption of hydrogen technologies therefore has the potential to facilitate significant emission reductions and contribute towards reaching climate change goals. Most of the technologies are still in the early stages of commercialisation and high costs have historically constrained the adoption. However, cost reductions and government incentives to encourage adoption the technology are expected to lead to substantial growth in the demand for hydrogen.

In this thesis, we consider a price taking Norwegian power producer who considers to become a supplier of hydrogen in the future. The company holds the option to invest in hydrogen production from electrolysis by installing a hydrogen plant with direct access to power from an existing wind farm. The hydrogen production is assumed flexible and operations can be costlessly suspended. In order to find the optimal investment timing, capacity and plant operations under uncertainty, we apply a real options approach. We propose a sequential model consisting of two parts. The first part optimizes the operation of the hydrogen plant over its lifetime. The second part derives the optimal investment timing and capacity of the plant using the least squares Monte Carlo (LSM). The optimal investment strategy is investigated through a case study of hydrogen production using wind power from Valsneset in Bjugn municipality in Norway. We study the investment under uncertain electricity prices and three hydrogen price scenarios.

Based on the results from the case study and the comparative statics analysis, we draw three main conclusions. First, the hydrogen price has to decrease significantly from today's level to make it optimal to delay the investment in the hydrogen plant. Second, the hydrogen price affects both the investment timing and the optimal capacity to invest in. Third, when the hydrogen price and variable costs approach each other, the investment decision considered becomes more sensitive to electricity price volatility. In this case, when the volatility is high, the investor installs a larger capacity. By installing a larger capacity he can produce greater amounts of hydrogen when electricity prices are low and avoid losses by suspending operations when prices are high. In other cases, when the volatility is not high enough for operations to be suspended, it has a smaller effect on the investment

decision.

Sammendrag

Hydrogen som produseres fra fornybar energi kan brukes som utslippsfritt drivstoff. Hydrogen kan brukes som drivstoff innenfor mange sektorer, men anses å ha størst potensiale som drivstoff i transportsektoren. Utbredt bruk av hydrogenteknologi kan derfor bidra til lavere utslipp og at klimamål nåes. De fleste teknologiene er fortsatt i en tidlig kommersialiseringsfase og høye kostnader har foreløpig hindret at teknologien har blitt tatt i bruk. På den annen side forventes det at kostnadsreduksjoner og statlige insentiver for å motivere til bruk av teknologien skal føre til at etterspørselen for hydrogen øker betraktelig i fremtiden.

I denne oppgaven ser vi på en norsk strømprodusent som vurderer å bli en leverandør hydrogen i fremtiden. Selskapet har muligheten til å investere i hydrogenproduksjon via elektrolyse ved å installere et hydrogenkraftverk med direkte tilgang til strøm fra en eksisterende vindpark. Hydrogenproduksjonen antas å være fleksibel. For å finne optimalt investeringstidspunkt, kapasitet og optimal produksjonsstrategi under usikre omstendigheter bruker vi en realopsjonstilnærming. Vi undersøker den optimale investeringsstrategien gjennom et casestudie av hydrogenproduksjon med vindkraft fra Valsneset i Bjugn kommune i Norge. Vi undersøker investeringen under usikre elektrisitetspriser og tre hydrogenprisscenarioer.

Basert på resultatene fra casestudiet og sensitivitetsanalysen trekker vi tre hovedkonklusjoner. Først finner vi at hydrogenprisen må synke betraktelig sammenlignet med dagens nivå før det blir optimalt å utsette investeringen i hydrogenkraftverket. Deretter finner vi at hydrogenprisen både påvirker optimal investeringstid og kapasitet. Til slutt finner vi at investeringen i hovedsak påvirkes av volatiliteten til elektrisitetsprisen når hydrogenprisen og de variable kostnadene nærmer seg hverandre. I dette tilfelle, når volatiliteten er høy, velger investoren å investere i en større kapasitet. Ved å installere en større kapasitet kan investoren produsere mer hydrogen når strømprisen er lav og unngå tap ved å stoppe produksjonen når pris er høy. I andre tilfeller når volatiliteten ikke er høy nok til at produksjonen stoppes, har den mindre effekt på investeringsbeslutningen.

Contents

Abbreviations

ADF	=	Augmented Dickey-Fuller test
EMPS	=	EFI's Multi-area Power-market Simulator
FCEV	=	Fuel cell electric vehicle
GBM	=	Geometric Brownian motion
HHV	=	Higher heating value
KPI	=	Key performance indicator
LHV	=	Lower heating value
LSM	=	Least squares Monte Carlo
LTSC	=	Long term seasonal component
MW	=	Megawatt
NPV	=	Net present value
RES	=	Renewable energy sources
STSC	=	Short term seasonal component

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Chapter 1

Introduction

Hydrogen produced from renewable energy can be used as an emission free fuel. While so-called green hydrogen has applications across several industries, its largest potential is seen within the transportation industry. Widespread adoption of hydrogen technologies therefore has the potential to facilitate significant emission reductions and contribute towards the ambitious climate change goals set by nations all over the world. The EU, for example, has set itself a goal of reducing emissions by 80-95% compared to 1990 levels by 2050[1]. In order to achieve these climate goals, mass application of hydrogen vehicles has been proposed by several action plans and road maps (IEA, 2015; Roadmap 2050, 2010b; The Norwegian Hydrogen Council, 2012).

Most of the hydrogen technologies are still in the early stages of commercialisation and are struggling to compete with existing technologies due to higher costs (IEA, 2015). In fact, both the production costs of green hydrogen and hydrogen vehicle costs remain high. First, compared to other production alternatives, producing hydrogen from renewable energy is more expensive. Second, the cost of the few commercially available hydrogen vehicles, remain high and refuelling infrastructure has not yet been rolled out on a large scale. As a result, there is considerable uncertainty regarding the adoption of these technologies and the size of the future market. However, several reports argue that the market will take-off from

[1] Low-carbon economy roadmap 2050 by the European Commission: `http://ec.europa.eu/clima/policies/strategies/2050/index_en.htm`.

2020-2030 due to large cost reductions and government support (The Norwegian Hydrogen Council, 2012; IEA, 2015; Fraile et al., 2015c).

In this thesis, we consider a price taking Norwegian power producer who considers to become a supplier of hydrogen in the future. The company wants to evaluate the opportunity to invest in a hydrogen plant using power from one of its existing wind farms. The investment is considered to be completely irreversible and the investor can choose when to invest and which capacity to invest in. The operation of the hydrogen plant is flexible. If the plant is installed the investor can at any time choose whether to sell the available power from the wind farm in the market or use it to produce hydrogen. However, electricity prices are assumed to be uncertain and give rise to uncertain profits. The investor must therefore optimally operate the plant in order to maximises his profit.

There are two main reasons why investment in hydrogen production from wind energy in Norway shows potential. First, the domestic and international hydrogen market is expected to grow (Fraile et al., 2015c; Tomasgard et al., 2016). The Norwegian Hydrogen Council (2012) argues that Norway can play a central role as exporter of hydrogen in a 2020–2030 perspective. Second, electricity prices are expected to remain low. In addition, they are expected to become more volatile in the future due to a higher penetration of variable wind power (Myhre, 2016). At times of excess supply the prices will drop and at times of insufficient supply the prices will peak. From the perspective of a Norwegian power producer low electricity price can potentially reduce its future profits. As a result, the power producer is looking for ways to adapt to the changing market conditions. Producing hydrogen when the price is low is therefore an alternative.

The investment opportunity in the hydrogen plant exhibits three interesting characteristics. First, the investment is completely irreversible. The initial investment cost is sunk and cannot be retrieved. Second, the profit streams are subject to uncertainty in electricity price. Third, the investor has can choose the investment timing and capacity and in addition operate the plant in a flexible manner. Under these circumstances, Dixit & Pindyck (1994) have shown that a real options approach leads to better investment decisions compared to traditional valuation methods such as the net present value (NPV). We therefore propose to solve this investment problem by proposing a real options model.

Our main contribution is twofold. First, we study the problem of determining optimal investment timing and capacity, in addition to optimising plant operations, by developing an adaptable model with electricity price as the underlying risk factor. The contributions to this strand of literature are limited. Chronopoulos et al. (2011) consider a risk-averse price taking firm that can choose optimal timing and capacity while incorporating risk aversion and operational flexibility in the form of suspension and resumption options. They consider one underlying risk factor, namely revenue uncertainty. Dangl (1999), allow for operational flexibility under demand uncertainty. In the model develop by Dangl (1999) the output is fixed by the upper capacity of the plant but can be adjusted according to uncertain demand. Hagspiel et al. (2016) elaborate on the paper by Dangl (1999) by analysing the specific implications of volume flexibility on investment timing and size. To do so they compare the optimal investment strategy for a flexible and inflexible firm. All of the aforementioned authors consider one underlying risk. They generally find that higher uncertainty makes it optimal to delay the investment longer and invest in a higher capacity. Compared to the work above we develop a less stylised. We propose a sequential model consisting of two parts. The first part is an optimisation that is formulated in order to model the operational flexibility offered by the hydrogen plant. It manages the complex task of deriving the optimal operation strategy over the whole lifetime of the hydrogen plant. The second part is a real options model which derives the optimal timing and capacity for the investment. Due to the complexity of the model we use a least squares Monte Carlo (LSM) to find the optimal investment timing and capacity. Moreover, we contribute by showing how the model can be applied to a real-life case study of a wind farm and hydrogen plant under uncertainty in electricity prices.

Second, we apply real options valuation to a specific hydrogen investment case, thereby adding to the ongoing discussion of the economic viability of hydrogen production from wind power. In particular, we add to the literature studying wind farms connected to the main grid and to the electrolyser. Due to the high uncertainty related to the profitability of hydrogen production from wind power, few investments have been undertaken. Several different framework conditions and optimal operating strategies have been studied. The viability of wind-hydrogen investments has mostly been studied based on levelised cost, which does not capture the inherent investment uncertainty. We contribute by proposing an optimisation model to find the optimal operation strategy of the wind-hydrogen system. Moreover, by using a real options approach to a specific case study, we contribute to further discussions of the economic viability of hydrogen production from wind power.

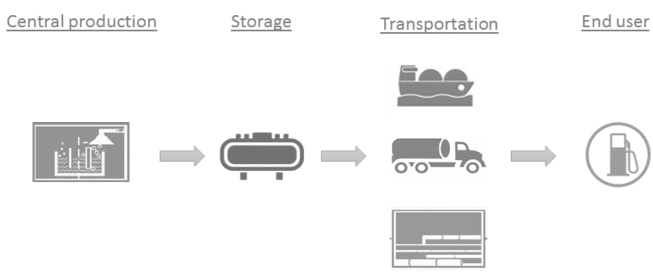
The remainder of the thesis is organised as follows. In Chapter 2, we present the framework conditions for the investment and give overview of the technologies used to produce hydrogen from wind energy. In Chapter 3, we provide an overview of the current and future market for hydrogen. Chapter 4 gives a summary of the academic literature related to hydrogen production from wind energy and related real options literature. In Chapter 5, we present our sequential model for optimal operations of the hydrogen plant and optimal investment timing and capacity. In Chapter 7, a case study is presented and a solution to our model is provided. Further, the chapter continues with a comparative statics of the optimal timing and capacity. Finally we present our conclusions and make suggestions for further research in Chapter 8.

Chapter 2

Production of hydrogen from wind energy

This chapter explains the fundamentals of producing hydrogen from wind energy. To set the context of the different technologies that will be discussed, we first present some basic facts about hydrogen. Second, we explain how the hydrogen plant and the wind farm could be operated together. Third, we present the technologies for producing hydrogen. Fourth, we outline how hydrogen can be stored and finally we discuss different methods for delivering hydrogen to the market. Figure 2.1 shows an overview of the topics we cover in this chapter.

Figure 2.1: Flow chart of the hydrogen value chain



2.1 Hydrogen - the basics

Hydrogen is the most abundant element in the universe. It has a density of 0.08988 kg/m^3 at standard temperature and pressure. Hydrogen becomes liquid at its boiling point, -253°C (Tzimas et al., 2003).

Because hydrogen is an energy carrier, we are interested in how much energy it can store. Table 2.1 shows the mass energy density and the volumetric energy density of hydrogen as a gas and as a liquid. The weight specific energy density of hydrogen is about 3 times higher than traditional gasoline. On the other hand its volumetric energy density is approximately a quarter of gasoline (Tzimas et al., 2003). Thus, in order for hydrogen to be economically stored and transported it needs to be compressed or liquefied.

The energy content of hydrogen is either reported in terms of higher heating (HHV) or lower heating value (LLV). When H_2O reacts with oxygen, water is formed and energy is released. The differentiation between HHV and LHV is based upon the state of the H_2O products of the reaction. If the H_2O product of the reaction is in liquid state the energy released is called the HHV. If the H_2O products of the reaction is in vapour state the energy released is called the LHV. Both are used in the literature.

Table 2.1: Volumetric and mass energy density of hydrogen

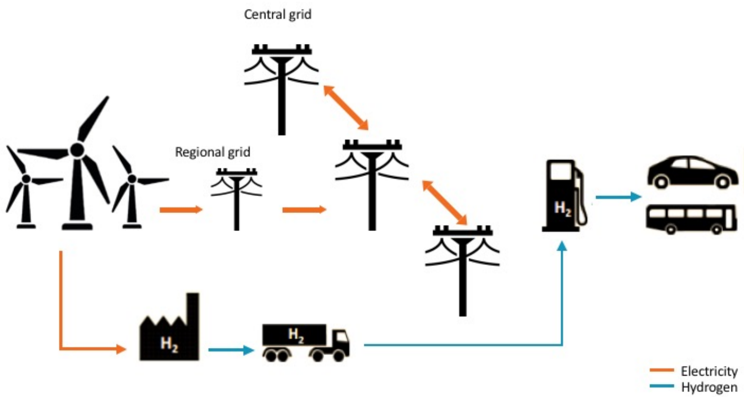
	Volumetric energy density (kWh/m^3)		Mass energy density (kWh/kg)	
	HHV	LHV	HHV	LHV
GH_2 at normal conditions	3.5	3.0	39.4	33.3
LH_2 at boiling point	2,789	2,359	39.4	33.3

Source: (Tzimas et al., 2003)

2.2 Operating the wind farm and the hydrogen plant together

There are several concepts for links between wind power and hydrogen production (Dahl et al., 2013). In this thesis, we consider a wind farm that is connected to the electrical grid and to the electrolyser. We will refer to this as wind-hydrogen system. The grid is assumed to have enough capacity to export all the power produced from the wind farm. The system configuration is shown in Figure 2.2.

Figure 2.2: Wind-hydrogen system configuration



Source: Dahl et al. (2013)

Wind farms produce variable amounts of electricity depending on the wind conditions. Its production patterns are not necessarily aligned with variations in demand, with regard to both location and time of supply. This causes periods of supply surplus and deficit, which is reflected in the market price of electricity.

The power produced from grid-connected wind power is normally traded on a power exchange. In Norway, electricity is traded on the Nord Pool Spot Exchange. The Nord Pool Spot Exchange consists of the day-ahead market and the intraday market (also known as the balancing market). The day-ahead market is the main area for electricity trading. Here, contracts are made between seller and buyer for the delivery of power on the following day. The intraday market supplements the day-ahead market and helps secure the necessary balance between supply and demand. In Norway, the power from wind farms is primarily only traded in the day ahead market and not sold in the balancing market (Nord Pool, 2016). The reason is that Norway's large portion of hydropower is sufficient to balance the supply and demand. In this thesis we therefore only consider the day-ahead market for trading power from wind farms.

The investor we are considering already owns a wind farm. Since the wind farm investment is assumed to already have taken place the related costs are sunk. We therefore isolate the value of investment in the hydrogen plant from the value of the wind farm. By investing in the hydrogen plant the firm gets the opportunity to use available power from the wind farm to produce hydrogen instead of selling it on a power exchange. The value of the hydrogen plant therefore depends on the extra profit generated from selling hydrogen and not electricity. However, even though we isolate the value of the hydrogen plant, the optimal operational strategy must still maximise the investor's combined profit from the operating the wind farm and the hydrogen plant. In Chapter 5 we develop a model that optimises the use of the available power.

2.3 Technologies for hydrogen production

In this subsection we focus on hydrogen production by electrolysis, which is the only way hydrogen can be produced from wind power. Today electrolysis only accounts for 4% of the world's hydrogen production.

For completion, we briefly mention the other ways to produce hydrogen from fossil fuels. Steam methane reforming, accounts for 48% of the world production, fraction of petroleum, accounts for 30%, and coal, accounts for 18% (IEA, 2015). In contrast to hydrogen production via electrolysis from renewable power, these production methods produce CO_2 as a by-product.

In the following subsection, we explain both the concept of electrolysis and the different technologies used in detail.

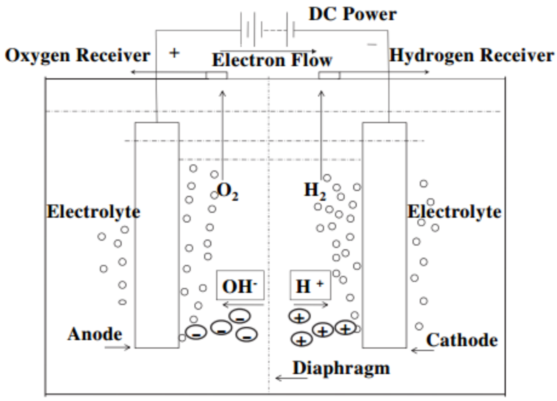
2.3.1 Hydrogen production from electrolysis

2.3.1.1 Electrolysis - the basics

Electrolysis is the process of splitting water into hydrogen and oxygen by applying a direct current. This process takes place in an electrolyser which consists of an anode, a cathode, power supply, and an electrolyte. The electrolyte generally consists of ions and is added to enhance the conductivity. These components together make up an electric circuit and Figure 2.3 illustrates a basic electrolysis cell.

The process of producing hydrogen can be described as follows: The electrolyte splits into positive and negative ions. These ions conduct electricity in a water solution by flowing from one electrode to the other. Electrons flow from the negative terminal of the DC source to the cathode at which the electrons are consumed by

Figure 2.3: Water electrolysis cell



Source: Zeng & Zhang (2010).

hydrogen ions (protons) to form hydrogen. Hydroxide ions migrate through the electrolyte solution to the anode, at which the hydroxide ions give away electrons. When hydroxide ions give away electrons, water and oxygen is produced. The role of the diaphragm is to separate the hydrogen and oxygen that is produced (Zeng & Zhang, 2010).

The chemical reaction can be described by the following equation:

$$H_2O \longrightarrow H_2 + \frac{1}{2}O_2 \tag{2.3.1}$$

The minimum theoretical voltage required for the reaction to take place is referred to as the reversible cell voltage and is equal to 1.23V (Zeng & Zhang, 2010) and the minimum energy required to produce hydrogen is then about 33 kWh/kg. In practice, the required voltage is always higher than the reversible cell voltage due to various sources of resistance in the cell circuits. Sources of resistance include electrical resistances in the circuit, reaction resistances at the electrode surfaces and mass transport resistance. An implication of this is that all commercial electrolysers have a minimum cell voltage for the reaction to take place.

2.3.1.2 The electrolyser plant

An electrolyser plant consists of two main components: One or more cell stacks and the balance of plant (BOP). A cell stack consists of up to more than 100 cells connected in parallel or series. The BOP includes other systems like an inverter to convert the input electricity from alternate to direct current, water treatment and storage. Stacks can be mounted in parallel using the same BOP infrastructure. Electrolysers are hence highly modular systems. While this makes the technology very flexible with respect to hydrogen production plant size, it also limits the effects of economies of scale, as even big electrolysers are based on identically sized cells and stacks (Körner, 2015)

In the following, we briefly explain key performance indicators (KPI) for electrolysers along the lines of Bertuccioli et al. (2014).

Capacity - Plant and stack size
The total capacity of both stacks and plant sizes varies depending on the production capacity needed. The largest stacks have a capacity of up to 2.3 megawatts (MW) and the largest plants have capacities up to 150 MW (IEA, 2015). While there is limited economies of scale regarding the number of cell stacks, constructing larger plants can bring some cost advantage with regard to BOP.

Efficiency
The efficiency of electrolysis is measured by power consumed per volume of hydrogen. The determinant of efficiency is the operating cell voltage. Increasing the voltage (keeping the current constant) reduces efficiency. There are three important factors that can influence the cell voltage: Operating temperature, operating pressure and the type and concentration of electrolyte. A higher operating temperature decreases cell voltage. A higher pressure reduces the size of the gas bubbles and minimises the resistance leading to a lower operating voltage. The choice and concentration of the electrolyte determine the resistance of the electrolyte.

It is important to keep in mind that the efficiency of electrolysers is not constant across all loads. Electrolysers are usually more efficient at lower loads (down to a certain minimum). Moreover, the efficiency of electrolysers decreases as it ages. This concept is known as voltage degradation and means that a higher cell voltage must be applied to maintain constant hydrogen production as the cell ages. After

6-7 years of operation the efficiency can be roughly 10% lower than at the start of life.

There is an important trade-off between electrolyser efficiency and hydrogen output. The rate of production is measured by volume produced per unit time and increases with current density. To understand this trade-off, recall that the electrolyser cell is an electric circuit where voltage and current are related by Ohm's law: $V = RI$. Hence if the voltage is increased, the current is automatically also increased. Therefore if the voltage increases the efficiency of the electrolyser is reduced, but at the same time its output increases.

Investment cost and operational expenditure

The cost of producing hydrogen by electrolysis is mainly determined by the variable cost of electricity and the initial investment cost associated with buying the electrolyser. Operational costs excluding electricity have been reported to be 2-5% of capital expenditure per year. The operational costs per MW installed decrease with plant size up to a certain level. The reason is costs such as labour do not increase linearly with the capacity installed.

In the future significant reductions of electrolyser costs are expected due to technological improvements and more efficient production. Today electrolysers are only built in small volumes and for niche markets. It is expected that much of the cost reduction potential in the future will stem from improvements in the whole supply chain and through increased production volumes for which more cost-efficient production techniques can be used (Bertuccioli et al., 2014).

Lifetime

Lifetimes of existing electrolysers have been reported to be up to 100 000 hours (Bertuccioli et al., 2014). Stacks rarely break down and the lifetime of electrolysers is typically defined in terms of the maximum efficiency drop due to voltage degradation that the operator allows. The acceptable efficiency drop before the stacks needs to replaced depends the trade-off between the cost lower efficiencies and the capital cost of replacing the stack. At the end of its life time only the electrolyser stacks needs to be replaced. The BOP and related infrastructure have a longer lifetime and do not need to be replaced (Bertuccioli et al., 2014). Replacing the electrolyser stack is referred to as regeneration.

Pressurised operation

Today pressurised electrolysers, typically delivering hydrogen at 3 MPa, are established on the market. Products delivering higher pressures are less mature, and can be considered as early commercial. Pressurised operation can reduce or eliminate the cost of an external compressor.

Dynamic and flexible operation

Historically, electrolyser systems have been designed to operate continuously at a set operating point to deliver a hydrogen stream of defined purity and pressure for industrial applications. However using an electrolyser with variable input energy requires it to be operated dynamically. The ability of an electrolyser system to operate dynamically can be captured through the four following metrics: Minimum part load operation, start-up time from cold, and ramping up and down time between minimum part load and full load.

2.3.1.3 Types of electrolysers

There are three types of electrolysers: (1) alkaline electrolysers (2) polymer/proton electrolyte membrane (PEM) electrolysers and (3) Solid oxide (SO) electrolysers. The electrolysers are mainly distinguished by their electrolyte and the charge carrier. Both alkaline and PEM electrolysers have been commercialised while SO electrolysers are still under research and development (R&D). Currently alkaline electrolysers have significantly lower investment cost and higher efficiency than the other two. However, PEM and SO electrolysers have higher potential for future cost reductions. In the case of SO electrolysers, it also has potential for future efficiency improvements. Table 2.2 compares the three electrolysers across the KPIs described above. In the following, we describe each type of electrolyser in more detail.

Alkaline electrolysers

Alkaline electrolysers use liquid electrolyte. They are currently the most mature and cost efficient way to produce hydrogen from electricity if hydrogen is produced at large quantities and at high loads (Körner, 2015). Alkaline electrolysers are currently used at industrial scale mainly to produce fertilisers from cheap electricity (Körner, 2015).

Table 2.2: KPIs of alkaline, PEM and SO electrolysers

KPIs	**Alkaline**	**PEM**	**SO**
Capacity (plant size)	Up to 150 MW	Up to 1 MW	Lab scale
Efficiency (HHV)	62-82%	68-78%	75-90%
Initial investment cost	750-1,350 €/kW	1,350 - 3,400 €/kW	-
Lifetime (hours)	60,000 - 90,000	20,000 - 690,000	1,000
Maturity	Mature	Early market	R&D
Output pressure (MPa)	∼0-3	1-3	4
Operating temp. (°C)	70-90	60-80	700-900
Minimum load (%)	20-40	5-10	3% *
Start-up time from cold (min)	20 - several hours	5-15	12 *
Ramp-up time from part load (min)	∼0-10%	10-100	0.1 *

Source: Körner (2015)
* Forecasted operation characteristics of SO electrolyser. Source: http://vbn.aau.dk/files/80222058/Technology_data_for_SOEC_alkali_and_PEM_electrolysers.pdf

The main advantages of alkaline electrolysis technology are availability, maturity, proven durability and low investment costs compared to other electrolysis technologies. Moreover the purity of the hydrogen produced is the highest compared to SO and PEM electrolysers. The main challenges are the low current density, low operating pressures and limited modes of dynamic operation.

PEM electrolysers

PEM electrolysers use a polymer membrane only permeable for hydrogen ions as the electrolyte. This differs from an alkaline electrolyser where a liquid electrolyte is used. PEM electrolysers have recently been introduced to the market, but have a much higher potential to become more cost efficient in the future compared to Alkaline electrolysers.

The main advantages of the PEM electrolysers are the greater production rates and flexibility with respect to minimum load, start-up time from cold and ramp up time from part load. The main challenges are related to the high investment cost and short lifetime.

SO electrolysers

In solid oxide electrolysers the electrolyte is a solid ceramic membrane. Solid oxide electrolysers are still in the laboratory stage, but are anticipated to become commercially available by 2020 (Bertuccioli et al., 2014).

The main difference of SO electrolysers to PEM and alkaline electrolysers is the high operating temperature of SO electrolysers. The heat can either be provided by internal electricity or from external sources. The main advantage with the high temperature is a higher efficiency. Moreover the investment costs of SO electrolysers could drop below PEM electrolysers in the future. Stack costs of SO electrolysers are currently are high but could drop to below PEM electrolyser costs in the future, due to the lack of precious metals and high energy density (Körner, 2015). On the other hand, there are also some challenges related to the high temperature. First the high operating temperature causes inflexibility in terms of start-up time from cold mode and load variation. The high temperature also increases costs due the need for materials that can withstand the heat, increased engineering complexity and reduced component lifetimes (Körner, 2015). The lifetime of the cell stacks is therefore the biggest challenge that must be overcome in order to make SO electrolysers a competitive alternative in the future.

2.4 Hydrogen storage

To store or transport hydrogen it must either be compressed or liquefied. Compressing or liquefying the hydrogen increases its volumetric energy density. We consider two storage options that can be used for medium-scale hydrogen production from wind power: Pressurised tanks for storing hydrogen gas and cryogenic tanks for storing liquid hydrogen. Both of the options can be used for medium-scale, medium-term and small-scale, short term storage. For both gaseous and liquid storage compressors are a key technology, and will be discussed at the end of this section.

Two other promising options for achieving high volumetric energies include metal hydrides and carbon nanostructures. These storage technologies are not considered here since metal hydrides are currently in the demonstration phase and carbon nanostructures are still under R&D (IEA, 2015). It is also possible to store hydrogen on a large scale in for example underground salt caverns or depleted oil fields. However, this alternative will neither be considered here because it will require a dedicated storage site Körner (2015).

Table 2.3 summarises the key parameters of the storage, compression and liquefaction technologies. The different technologies are described in further detail below.

Table 2.3: Hydrogen storage technologies

Application	**Power**	**Efficiency (%)** *	**Initial investment cost**	**Lifetime (years)**	**Maturity**
Compressor, 18 MPa	-	88-95	~60 €/kW	20	Mature
Compressor, 70 MPa	-	90-91	150-350 €/kW	20	Early market
Liquefier	15-80 MW	~70	800-1,800 €/kW	30	Mature
Pressurised tank	0.1-10 MWh	Almost 100	5,400-9,000 €/Mwh	20	Mature
Liquid storage	100-10^5 MWh	Boil off stream: 0.3% loss per day	700-9,000 €/MWh	20	Mature

* Efficiencies are based on lower heating value. The energy required by the application per kg of hydrogen is therefore $(1 - \text{efficiency}) \cdot LLV$
Source: Körner (2015)

Pressurised tanks

Pressurised tanks are the most common and mature hydrogen storage technology. Current storage capacities are between 100 kWh and 10 MWh. Storage pressures lay between 20 MPa and 70 MPa. Pressurised tanks are both used for stationary storage and in mobile applications such as in fuel cell electric vehicles (FCEVs) that run on hydrogen and to transport hydrogen with tube trailers.

If compressed gas is injected into pressurised tanks, the tanks are almost 100% efficient. Hence, no energy is lost or required to store the hydrogen in pressurised tanks. The investment costs of pressurised tanks are strongly dependent on pressure. At lower pressures (around 20 Mpa) investment costs lay around €5-9/kWh of hydrogen. At higher pressures (around 70 MPa) the investment cost lay around €17/kWh of hydrogen (Körner, 2015).

Cryogenic tanks

Liquefied hydrogen can be stored in cryogenic tanks. This requires a temperature as low as minus 253 degrees C° under atmospheric pressure. Achieving this extremely low temperature requires several stages of compressions as well as heat exchangers and multiple cooling cycles. This is an energy intensive liquefaction process, and it uses energy equivalent to 25-40% of the hydrogen stored (Körner, 2015).

Cryogenic tanks have a capacity of up to 100 GWh. However, cryogenic tanks provide limited storage time of up to a few days due to the boil-off gas losses. Cryogenic tanks are isolated pressure tanks. The gas therefore behaves approximately according to the ideal gas law. As temperature rises the pressure increases.

Therefore, very low temperatures can be sustained in the tank through constantly so-called releasing boil-off gas. The efficiency of the storage tank depends time since around 0.1% to 0.5% of the stored hydrogen needs to be released per day. Investment costs range between €0.9-9/kWh (Körner, 2015).

Compressors and liquefiers

Compressors and liquefiers consume electricity to convert, compress or liquefy the hydrogen. We do not go into detail about how the compressors and liquefiers work, but present their current performance in Table 2.3. From Table 2.3 it can be observed that the energy required for compressing 1 kg is about 10% of its LHV. The energy required to liquefy 1 kg of hydrogen is about 30% of its LHV.

2.5 Transport and distribution

Since the investor considered in this is potentially going to produce hydrogen at an existing wind farm site, the hydrogen must be transported and distributed to refuelling stations. To supply nearby refuelling stations, gaseous truck transport, liquefied truck transport represent two available alternatives. For economic export of hydrogen to other parts of the world pumping gaseous hydrogen through pipelines or transporting liquid hydrogen on ships are two alternatives (The Norwegian Hydrogen Council, 2012). Table 2.4 summarises the key parameters of the different transportation and distribution options that are currently available. These alternatives will be described in more detail in the following subsections.

Table 2.4: Hydrogen transportation technologies

Application	**Capacity (kg)**	**Efficiency**	**Initial investment cost**	**Lifetime (years)**	**Maturity**
Hydrogen tube trailer (gas)	≤ 1,000	~100%, excl. compression	900,000 €	-	Mature
Liquid tankers for hydrogen delivery	≤ 4,000	Boil off stream: 0.3% loss per day	680,000 €	-	Mature
Pipeline	-	95% incl. compression	Rural: 1.08 M €/km Urban: 680,000-1.35 M €/km	40	Mature
Ship	≤ 177,500*	-	- -	-	R&D

* Estimated capacity of a planned demonstration H_2 tanker by Kawasaki Heavy Industries.
Source: `http://www.greencarcongress.com/2013/09/20130928-khi.html`
Source: Körner (2015)

2.5.1 Gaseous tube trailers

Gaseous tube trailers have pressures of up to 60 MPa and are so far limited to capacities of up to 1,000 kg. However, the capacities of average existing tube trailers lay in the range of 300 kg to 600 kg. Körner (2015) estimates that a 600 kg truck would be sufficient to refuel less than 120 vehicles. He shows that hydrogen would need to be delivered several times a day, since an average petroleum station in Europe serves 200 cars per day.

The cost of a gaseous truck is around €900/kg of hydrogen. Körner (2015) concludes that gaseous truck transport is viable alternative for lower hydrogen demand and short transportation distances.

2.5.2 Liquefied truck trailers

Liquefied truck trailers can achieve capacities of up to 4,000 kg of hydrogen. However, as we have already explained, the liquefaction of the hydrogen is costly and liquefied transportation is also subject to boil-off losses. Körner (2015) concludes that liquefied trucking is the preferable alternative for high transport distances even if demand stays moderate.

2.5.3 Hydrogen pipelines

Hydrogen pipelines are very efficient but the large upfront investment cost and the risk linked to future utilisation are challenging. Either hydrogen can be mixed into natural gas pipelines or use dedicated pipelines for hydrogen. An option for Norway is to inject surplus hydrogen into existing gas-pipelines to Europe (Dahl et al., 2013). However, a domestic or international gas-grid dedicated to hydrogen transport in Norway is not currently in place, and as seen from Table 2.4 this would require large investments.

Körner (2015) concludes that pipeline transport is most efficient at high hydrogen flows over a broad range of distances.

2.5.4 Liquefied hydrogen on ships

To this date, liquefied hydrogen transport on ships in under R&D. Kawasaki Heavy Industries is planning to have a demonstration ship ready in 2017.[2] The available information about the ship is shown in Table 2.4.

[2] Planned liquid H_2 tanker by Kawasaki Industries: `http://www.greencarcongress.com/2013/09/20130928-khi.html`

Chapter 3

The market for hydrogen

In 2013 global hydrogen consumption amounted to 60 million tons (Fraile et al., 2015c).[3] Hydrogen is currently almost all used as a feedstock in the industry. Most of the industry demand comes from the chemical and refining industries (Fraile et al., 2015c).

In addition to the use of hydrogen in industrial processes, the use of hydrogen as an energy carrier is emerging. As an energy carrier, hydrogen can be used in sectors where there is demand for energy and Fraile et al. (2015c) identify two additional segments for hydrogen. First, hydrogen can be used as an emission-free fuel in the transportation sector. Second, hydrogen can be blended into the natural gas-grid to enhance natural gas. The current demand in these segments is negligible, but is foreseen to grow in the future. Note that another possible segment could be co-generation of heat and electricity in buildings using hydrogen. This segment is not considered here, due to limited information available about the current and future demand.

In general, very few hydrogen market studies are publicly available. To the best of our knowledge, we use the most recent data available for our analysis. The main market estimations cited in this report are gathered from two reports developed in a collaborative effort between the European union and New Energy World-JU, named CertifHy.[4] In the first report, Fraile et al. (2015c) show how the current

[3] Global demand was converted to metric tons using a hydrogen density of 33.3 kWh/kg.

[4] Unless otherwise cited, the market estimations are taken from these reports.

market is segmented and forecasts how the hydrogen demand will evolve in the period 2015 to 2030. The second report by Fraile et al. (2015b), focuses on the future penetration rates of green hydrogen.

The overall aim of this chapter is to identify possible markets to which a Norwegian investor could sell hydrogen produced from wind power. We first consider each of the segments for the European market and discuss their outlook. In the analysis, we distinguish between total hydrogen demand and the demand for green hydrogen. Second, we briefly consider Japan as another possible market. Next, we consider the demand for hydrogen in Norway. Finally, based on the analysis of the market segments, we develop future price scenarios that serve as input to our model.

3.1 The European hydrogen market

3.1.1 The industry segment

The industry segment in Europe can further be divided into four sub-segments: Chemical, refining, metal processing and "other". According to Fraile et al. (2015c) the chemical segment is the largest with an industry share of 63%. In the chemical industry, hydrogen is mainly used to produce ammonia and methanol. Refineries are the second largest consumer with an industry share of 30%. In the refining industry, hydrogen is used for hydro-treating, hydro-cracking and desulphurisation during the refining process to produce cleaner fuels. Metal processing encompasses the use of hydrogen to yield iron reduction and is the third largest sub-segment with an industry share of 6%. The "other" segment includes the use of hydrogen in the electronics, aerospace, glass, food and heat treatment industries. These industries account for 1% of the total industry share. The industry consumption in Western Europe in 2010 was 7 million tons or 16% of the world consumption (Fraile et al., 2015c). Asia and Pacific are the world's leading consumers representing 1/3 of global consumption.

The main three producers are merchant companies, captive producers, and by-product hydrogen producers. Most of the hydrogen is produced by captive producers (64%), that produce hydrogen for their direct customer or their own use. The captive producers are followed by the commercialised by-product (27%) producers and the merchant suppliers (9%). In the industrial segment, it is widely accepted that Steam Methane Reforming (SMR) is the main production method and will continue to be so for years to come (Fraile et al., 2015a).

In contrast to many other commodities, hydrogen is not traded on an exchange. The price of hydrogen is often established through contracts and depends on the location of delivery and the purity of the hydrogen delivered. This makes the market less transparent and market prices are not publicly available. Nevertheless, Fraile et al. (2015c) report that prices are known to vary between €10/kg and €60/kg depending on the location of delivery and purity of hydrogen. The production cost of hydrogen using SMR is expected to remain stable, and is forecast by Dillich et al. (2012) to be around €2.6/kg in 2030.[5]

The global hydrogen market in the industrial sector is expected to grow at a rate of 3.5% per year until 2025 (Fraile et al., 2015c). The primary driver of this growth will be the petroleum refining industry due to increasing demand for cleaner fuels (Freedonia, 2012). Assuming a similar trend Fraile et al. (2015c) estimate that the European industrial market will grow to 8 million tons in 2025. Fraile et al. (2015b) estimate that the proportion of green hydrogen in this segment could reach 30% by 2025 and increase to 40% beyond 2030.

3.1.2 The transportation segment

The EU has set a target to reduce greenhouse gas emissions by 80-95% when compared to 1990 levels by 2050[6]. The transportation sector, including road, sea and air transport, accounts for about 25% of EU's greenhouse gas emissions[7]. EUs low carbon economy roadmap suggests that emissions in the transportation sector could be redcued by up to 60%. The decarbonisation requires mass application of electric vehicles, hydrogen fuel cell vehicles and/or biofuels (Roadmap 2050, 2010b). The main driver for hydrogen demand will come from the use of FCEVs that run on hydrogen. We consider FCEVs to include trains, cars, buses, lorries, other utility vehicles and ferries and ships that run on pure hydrogen.

The future of FCEVs is dependent on investments in refuelling infrastructure and commercialisation of vehicles. In 2014 around 550 FCEVs (passenger cars and

[5] The price of hydrogen per kg was converted to €/kg using an average exchange rate of 1,286 €/$ in 2012.

[6] Low-carbon economy roadmap 2050 by the European Commision: `http://ec.europa.eu/clima/policies/strategies/2050/index_en.htm`.

[7] Current greenhouse gas emissions in the EU by sector: `http://ec.europa.eu/clima/policies/international/paris_protocol/transport/index_en.htm`.

buses) were running in demonstration projects across the world (IEA, 2015). As of 2016 there are only three FCEV commercially available[8]. The vehicle costs remain high and FCEV prices announced have been set around €66,000[9] ex. VAT. The risks associated with market uptake of FCEVs have been a significant barrier to infrastructure investment. (IEA, 2015) estimates that investments in refuelling infrastructure would be in the orders of tens to hundreds of billions of dollars.

Despite these initial challenges, Fraile et al. (2015c) present three EU-wide and national studies that expect that the penetration of hydrogen vehicles will increase in the future[10]. HyWays (2008) estimates that the number of FCEVs in EU could reach 5-7 million vehicles (3-7% penetration) in 2025 and possibly 12-25 million vehicles (9-13% penetration) in 2030, depending on the learning rate and policy support. In terms of hydrogen demand, this translates into 0.6-0.8 million tons and 1.4-3 million tons per year for 2025 and 2030, respectively.[11] A report by McKinsey & Company (2010) estimates the total number of vehicles to reach 1 million in 2025 and 68 million[12] in 2050. This would translate into a demand of 8.1 million tons. In addition Fraile et al. (2015c) present a collection of several national hydrogen transportation studies. By aggregating these national studies Fraile et al. (2015b) estimate the demand for both green and normal hydrogen. Their forecast is shown in Figure 3.1.

Fraile et al. (2015c) also present several studies that forecast the future price of hydrogen. As already explained, the hydrogen price is directly dependent on production and distribution costs. In the short-term the cost of dispensed hydrogen at the refuelling station is expected to be high due to the underutilisation of retail stations. In the long term the retail price is projected to gradually decrease from today's level of €10/kg to €5-7/kg by 2030 (Fraile et al., 2015c).

[8] Toyota Mirai, Hyundai ix35 FCEV and Honda Clarity `https://en.wikipedia.org/wiki/Hydrogen_vehicle`.

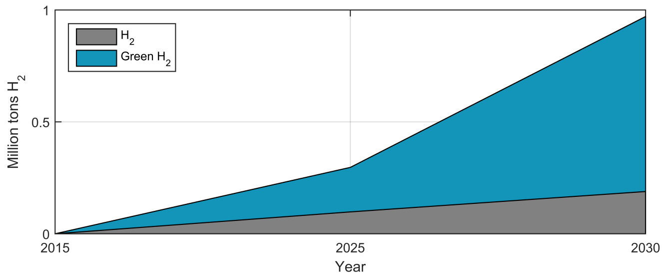
[9] Price of Toyota Mirai at launch: `https://www.toyota.no/world-of-toyota/articles-news-events/2014/mirai.json`.

[10] Hyways, McKinsey and H2Mobility scenarios.

[11] Assuming that an average passenger vehicle in the EU travels about 12 000 km/year, and that the FCEV consumes about 1 kg hydrogen/100 km.

[12] McKinsey & Co estimates a penetration rate of 25% and the number of passenger cars in Europe to be 273 million in 2050.

Figure 3.1: Estimated demand for hydrogen in the European transportation segment



Source: Fraile et al. (2015b)

3.1.3 The enhanced natural gas segment

The market for enhanced natural gas is also referred to as the power to gas segment. As already mentioned, hydrogen producers may decide to inject hydrogen into the natural gas grid. This can be done if there is not enough demand from other higher value users. The hydrogen blended into the grid can be used for heating applications or any other application of natural gas.

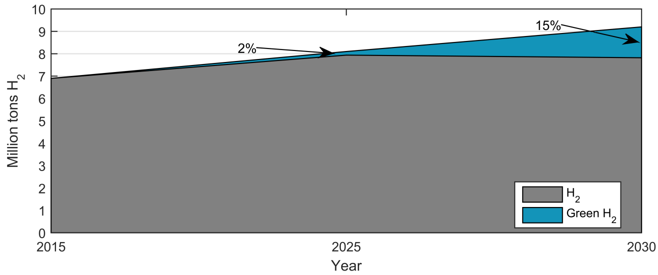
To this date, gas grid injection is not widely spread, and volumes of hydrogen produced and injected are negligible. Moreover, it is difficult to assess future hydrogen gas grid injections. Fraile et al. (2015c) have estimated the total amount that could be technically injected into the grid. For this forecast, they assume that about 80% of the total hydrogen injected to the natural gas is produced from renewable electricity. The demand for green hydrogen in the enhanced natural gas segment is estimated to be 0.16 million tons in 2025 and 0.34 million tons in 2030 (Fraile et al., 2015b). It is important to highlight that these figures, rather than showing market penetration expectations, are reflecting the technical capacity.

3.1.4 Summary of the demand from the three segments

The total demand estimated for hydrogen in Europe is given by Fraile et al. (2015b) in Figure 3.2.

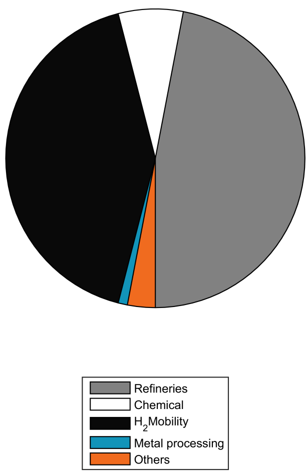
The share of green hydrogen between the market segments is shown in Figure 3.3.

Figure 3.2: Estimated total demand for hydrogen in Europe



Source: Fraile et al. (2015c)

Figure 3.3: Share of green hydrogen in the European market segments in 2030



Source: Fraile et al. (2015b)

3.2 The Japanese market

In addition to the European market, Japan is another possible international market. Japan has ambition of establishing a zero-emission hydrogen supply chain by 2040, and is currently a net importer of energy (Hamanaka, 2015). The Japanese hydrogen market is expected to grow to 1.3 million tons in 2030 and 13.5 million tons in 2050 (DNV-GL, 2015). Japan is also planning to demonstrate hydrogen technology under the Summer Olympics in 2020 possibly using hydrogen that is made in Norway[13].

3.3 The Norwegian market

One of the most recent report that studies the demand for hydrogen in the transportation sector in Norway is Tomasgard et al. (2016). With respect to the industry and hydrogen enhanced natural gas segment, the authors have not been able to find detailed information. However, in 2007 83,000 tons of hydrogen were produced in Norway, and Maisonnier et al. (2007) list Norwegian producers and their capacities. Most of these producers supplied the industry segment (Maisonnier et al., 2007).

3.3.1 The transportation segment

In Norway the target is to become climate neutral by 2030. To achieve this a drastic reduction of emissions in the transport sector will be necessary (Tomasgard et al., 2016).

In a recent study Tomasgard et al. (2016) estimate the future deployment of FCEVs in the four largest cities in Norway from 2016 to 2030. The report considers three scenarios for the adoption of FCEVs: High, medium and low. For each scenario the report estimates the number of passenger cars, taxis, buses, lorries and ferries.

Based on the adoption of FCEVs in the different scenarios the total hydrogen demand is estimated to be equal to 9,500 tons in the low scenario, 30,000 tons in

[13] Norwegian hydrogen as fuel in the Summer Olympics 2020: http://www.aftenposten.no/norge/Norsk-hydrogen-blir-en-viktig-OL-deltager-i-Tokyo-61345b.html.

the medium scenario and 61,000 tons in the high scenario.

3.3.1.1 Other possible uses of hydrogen in the transportation segment

The report also mentions three other potential areas of use that could increase the demand for hydrogen in the Norwegian market further. First hydrogen can be used to enhance the efficiency of bio gas production used for buses. Today the municipality of Oslo produces 6,000 million Nm^3 biogas annually, and is planning to double the production by 2018 (Tomasgard et al., 2016). Injecting hydrogen could increase the amount of biogas produced with 50%. Second, hydrogen can be used to propel construction vehicles. The potential for construction vehicles is estimated to be about 2/3 of the potential in the lorry segment. Third, hydrogen can be used for trains. Møller-Holst & Thomassen (2015) study alternative fuels for train routes that cannot be electrified. Møller-Holst & Thomassen (2015) find that hydrogen trains could constitute one of the best alternatives already by 2021. However, by 2027 and 2050 they should become even more competitive compared to other alternatives. The study considers four routes: Nordlandsbanen from Bodø to Trondheim, Rørosbanen from Strøen to Hamar, Solørbanen from Elverum to Kongsvinger and Raumabanen from Åndalsnes to Dombås. We have summarised the potential hydrogen demand that could arise if these trains would use hydrogen as fuel in Table 3.1. For Rørosbanen and Nordlandsbanen it will be sufficient to have one refuelling station at Trondheim central station.

Table 3.1: Potential hydrogen consumption from railway in Norway

	Energy consumption per roundtrip (MWh)	**Number of roundtrips per day**	**Hydrogen consumption per day (tons)**	**Hydrogen consumption per year (tons)**
Nordlandsbanen	30	5	1.9	563
Rørosbanen	18	10	1.1	338
Solørbanen	20	2	1.3	375
Raumabanen	3.3	3	0.2	62

Source: Møller-Holst & Thomassen (2015)
To calculate the potential hydrogen demand, we have assumed a fuel cell efficiency of 50% and energy density of 32 kWh/kg.

3.4 Price scenarios

In this subsection we demonstrate the potential demand for hydrogen produced by an investor and then create different scenarios for the price of hydrogen that serve as input to our model.

Based on the market analysis above it would be feasible for an investor to supply both the European, the Japanese and the Norwegian market. Table 3.2 shows the estimated market size for green hydrogen in these markets in 2030. In all of the markets the transportation segment is foreseen to have the largest growth. To illustrate what these market sizes could mean in terms of demand for hydrogen produced by an investor, we arbitrary assume that the firm can capture a market share of 1%. This demand could be used as a general idea about how much hydrogen the firm could produce.

Table 3.2: Market size for Europe, Japan and Norway and possible market shares in each country

	Europe 2030	**Japan 2030**	**Norway 2030**
Market size (tons)	786,000*	195,000*	30,000†
Demand (tons) for 1% market share	7,860	1,950	300

* We have assumed that green hydrogen has a 15% share of the total market.
† We have assumed that all of the demand consist of green hydrogen

When the firm is going to decide which markets to supply it must consider future production and distribution costs. For small-scale production it would most likely be most beneficial to supply the Norwegian market. However, for large-scale production it might be a possibility to export hydrogen to Europe and Japan. In fact, recently SINTEF energy and several partners[14] were awarded 14 million NOK to conduct a feasibility study of the potential for large scale hydrogen production in Norway for export to the European and Japanese markets.[15]

The future retail price of hydrogen is uncertain. The uncertainty is related to both the average price level and other characteristics such as price volatility. Trying to forecast the dynamics of the price is therefore difficult. For modeling purposes, we will assume that the hydrogen price will be constant in the future. Based on the

[14] NEL, Statoil, Linde Kryotechnik, Mitsubishi Corporation, Kawasaki Heavy Industries, NTNU and The Institute of Applied Energy, among others.

[15] Summary of the Strategic Road Map for Hydrogen and Fuel Cells by the Japanese Agency for Natural Resources and Energy: `http://www.meti.go.jp/english/press/2014/pdf/0624_04a.pdf`.

estimates of the future hydrogen price prices presented in Section 3.1.2 we create three possible future scenarios:

- Scenario 1: We assume that the retail price remains at today's level: €10/kg.
- Scenario 2: We assume that the retail price falls to its highest estimated value: €7/kg.
- Scenario 3: We assume that the retail price falls to its lowest estimated value: €5/kg.

We emphasise that these are estimates of the future prices and that they are subject to uncertainty. Recall that the prices quoted above are estimates of retail prices. We therefore expect that a company supplying the hydrogen refuelling stations will receive a lower price. To estimate the price a hydrogen producer will get, we assume that a hydrogen refuelling station requires a similar margin to today's gasoline stations. Today the margin for gasoline stations in Norway is about 13%[16]. Hence, the estimated prices that will be used in our model are:

- Scenario 1: We assume a hydrogen price of €8.8/kg.
- Scenario 2: We assume a hydrogen price of €6.1/kg.
- Scenario 3: We assume a hydrogen price of €4.4/kg.

[16] Gas station margins in Norway: `http://www.side3.no/motor/joda-bensinstasjonene-tar-seg-bedre-betalt-for-bensinen-na-enn-fr/3422816285.html`.

Chapter 4

Related literature

Our work contributes to two strands of literature. First, we extend the literature studying hydrogen production from wind power. Second, we add to the existing real options literature. In this section, we review the two strands.

4.1 Hydrogen production from wind power

Several studies about producing hydrogen from wind energy have been published. Here, we divide the literature into two main categories. The first category focuses on grid connected hydrogen plants. The second category focuses on hydrogen plants connected to wind farms. We refer to these as wind-hydrogen systems. Different wind-hydrogen systems are mainly distinguished by whether the wind farm is grid-connected or stand-alone.

Since this is a relatively new field of literature, our aim is to give an overview of the different studies available.

4.1.1 Studies of grid-connected hydrogen plants

Concerning the first strand of literature several authors have studied the potential of grid-connected electrolysers. The studies focus on utilising price fluctuations caused by variable wind power in order to produce low cost hydrogen. Floch et al.

(2007) study the opportunity to produce hydrogen during off-peak periods using power from the day-ahead markets in France, Scandinavia, USA and the balancing market in Canada. The off-peak period is defined as the time during which the electricity price falls below a certain threshold. The study uses historical electricity prices. The trigger level is found by minimising the levelised cost of production.[17] By optimising production periods, they find that savings from producing during off-peak periods vary enormously across markets. Some highly fluctuating markets offer very low prices during off-peak periods and allow for viable hydrogen production, even if average electricity prices first appear to be high. For other, more stable markets, producing hydrogen during off-peak periods does not lead to significant cost reductions. For stable markets the installation is stopped during the high-price peaks rather than taking advantage of off-peak prices. Jørgensen & Ropenus (2008) study the opportunity to produce hydrogen from grid-connected electrolysers in the Danish power market. By parameterising the existing spot price structure and estimating the annual capital costs they derive the number of hours per year the electrolyser should be operated in order to minimise the levelised production cost. They conclude that savings on the power price by operating electrolysers part time are not likely to decrease the hydrogen production price significantly. Moreover if the electrolyser is operated for fewer hours, investment costs per produced unit of hydrogen will increase. Gutiérrez-Martín et al. (2009) study viability of large-scale grid-connected hydrogen plants using surplus energy in the French power market. They simulate the operation of a 100 MW plant that only produce hydrogen when the electricity price approaches zero. Similar to Jørgensen & Ropenus (2008) they also apply a levelised cost of production approach. They find that by adjusting output according to electricity cost the hydrogen production costs are minimised. They conclude that intermittent operation of electrolyser shows great potential to achieve low hydrogen production costs. Based on these three studies we can conclude that the potential cost reductions achieved by operating the electrolyser part time, depend on the price characteristics in the specific market studied.

4.1.2 Studies of wind-hydrogen systems

With regard to the second strand of literature the papers can be distinguished based on the operational strategy of the wind-hydrogen system and whether the wind farm is grid-connected or not.

[17] The net present value of the unit-cost of production.

Several authors study the production of hydrogen from grid-connected wind-energy farms when facing limited transmission capacity to the main grid. Løland (2015) and Gutiérrez-Martín et al. (2010) consider the simple operation strategy to produce hydrogen when the power output from the wind farm exceeds the capacity of the grid. Løland (2015) studies an investment in the expansion of an existing wind-farm and a hydrogen plant. She finds levelised cost of production to lay between €4.23 – 4.34/kg. Similar to this thesis, Gutiérrez-Martín et al. (2010) studies the investment in a hydrogen plant located inside and existing wind farm. They consider the potential profit from storing hydrogen that can be converted back into electricity during peak hours. Using an NPV approach to evaluate the investment they conclude that the hydrogen should be installed. Similar to Gutiérrez-Martín et al. (2010), Korpås (2004) allows for storage of hydrogen that can be converted back into electricity when the wind power production is low. However, Korpås (2004) considers several other operational strategies including for example maximising hydrogen production and balancing the grid. He also considers a hypothetical case and calculates its levelised cost of production depending on the operational strategy chosen.

In contrast to the previously mentioned studies, Bernal-Agustín & Dufo-López (2008) consider generation and storage when there are no grid restrictions. The operating strategy is to store hydrogen during low demand hours, while during high demand hours the stored hydrogen can be used to generate electricity. They value the wind-hydrogen system using an NPV approach and find that the electricity price of the electricity produced from stored hydrogen must be relatively high in order for the system to have the same NPV as a wind-only system. A related study by González et al. (2004) considers production of on-site hydrogen from wind farms in Ireland. In contrast to Bernal-Agustín & Dufo-López (2008) they do not consider converting hydrogen back to electricity. Instead, the hydrogen produced can be sold to end users. By comparing the trade-off between levelised cost of production to the revenues generated for different hydrogen prices they find the optimal size of the hydrogen plant.

Greiner et al. (2007) consider a Norwegian case study on the production of hydrogen from wind power. They compare hydrogen production from a grid-connected system to a system that is not grid-connected. The operational strategy in both cases is to produce hydrogen at a constant rate and use back up from the grid or a diesel generator when the wind production is too low. The cost of hydrogen produced is calculated using the levelised cost of production.

Examples of studies that consider stand-alone systems are Dutton et al. (2000) and Pedrazzi et al. (2012). Dutton et al. (2000) study the performance of an electrolyser connected to a single windmill. Their work is based on a demonstration site in Italy. Since there is no external demand, the operation strategy is to use all the wind power to produce hydrogen. Using the levelised cost of production they conclude that production costs of the system cannot compete with hydrogen production from fossil fuels. Pedrazzi et al. (2012) also study a stand-alone system. They focus on a wind-hydrogen system aimed at supplying electrical and thermal residential loads. Pedrazzi et al. (2012) do not consider the economics of the system, but focus on simulating the system to find its efficiency.

In summary, the second category focusing on hydrogen plants connected to wind farms consider different framework conditions. The operational strategy depends on the specific investment case studied. However, most of the literature uses a levelised cost of production to evaluate the investments.

Our main contribution to this area of literature is that we apply real options valuation to a specific hydrogen investment case that accounts for uncertainty in the electricity price. We thereby add to the ongoing discussion of the economic viability of hydrogen production from wind power. In addition, along the lines of González et al. (2004), we also propose an optimal operating strategy that is based on maximising profits rather than minimising production costs.

4.2 Valuing flexible investment opportunities under uncertainty using a real options approach

In this thesis, we study the combined problem of determining optimal investment timing and capacity choice, in addition to deriving an optimal operating strategy for the hydrogen plant. The investment decision is also subject to electricity price uncertainty.

In this subsection, we first give an overview of the real options literature that studies optimal operations. Second, we review the literature that studies both optimal timing and capacity choice. Third, we present work that consider optimal timing and capacity choice under operational flexibility. Last, since our model can possibly account for multiple-underlying risk factors we present studies that have demonstrated its applicability.

4.2.1 Operational flexibility

For projects that can be operated in a flexible manner, authors are concerned with developing an optimal operating policy in order to maximise the project value. The real options problem is typically formulated as an optimal control problem with multiple risk factors. Different solution methods and applications have been studied. In Dixit & Pindyck (1994) the option to temporarily suspend operations, if the project is making a loss, is considered. They derive an analytical solution for the optimal operating policy as well as the time to invest by solving a partial differential equation (PDE). Several other authors find analytical solutions for stylised cases. Thompson et al. (2009) use a real options approach to value and find the optimal operation of a natural gas storage facility. Thompson (2013) studies the optimal operation of a gas-fired power plant. Fleten & Näsäkkälä (2010) study investment timing and operating flexibility of gas-fired power plants.

Another solution approach applied by Nadarajah et al. (2015) is linear programming. Nadarajah et al. (2015) uses linear programming to find the operating policy to manage storage of commodities that can be potentially sold in the future at a higher price. A related approach is stochastic programming. This technique is applied by both Fleten et al. (2002) and Sen et al. (2006) to derive the optimal strategy to schedule production.

Further, a solution approach which will also be applied in this paper, is least squares Monte Carlo. The approach is for example applied by Aas & Andresen (2015), who uses it to solve a stochastic dynamic program to find both the value and the optimal operation of an aluminum smelter. Bakke et al. (2016) also use Monte Carlo simulations, but do so in combination with a linear program to value the option to delay investment in battery storage. The role of the linear program is to optimise the operation of the battery storage over a period of one day. The daily profit is then summarised over the first year of operation. The first year profit is then used to derive the project value. The maximised project value then serve as input to the real options investment model. By optimising the operation of the battery plant over a period of one day the computational complexity of the problem is reduced. In contrast, if the operations were to be optimised over the lifetime of the battery storage, the problem would potentially consist of thousands of time steps. Moreover, instead of assuming that the investment decision can be undertaken every hour, Bakke et al. (2016) discretise the investment decision problem so that the investor can only exercise the option to invest once a year.

In this thesis, we also use Monte Carlo simulations in combination with a linear program that optimises the operation of the hydrogen plant. However, in contrast to Bakke et al. (2016) we optimise the operations over the whole lifetime of the project (20 years). Note that solving for the optimal operation over the lifetime of the project using a linear program is equivalent to mathematically formulating a dynamic programming problem as was done in Aas & Andresen (2015). Similar to Bakke et al. (2016) we assume that an investor can only undertake the decision to invest once every year. Thus, while operations are optimised on an hourly basis the investment decision can only be undertaken once every year.

4.2.2 Flexible timing and capacity choice

Most real options papers focus on the optimal timing of an investment. McDonald & Siegel (1986) and Dixit & Pindyck (1994) are considered to be pioneers in the field and study the option to delay irreversible investments under uncertainty. Dixit & Pindyck (1994) employ dynamic programming to model investment decisions, and find develop analytical solutions to find the optimal investment timing. Dixit & Pindyck (1994)'s optimal timing model has been extended in different ways to take into account investor's option to choose the optimal size/capacity of the investment.

Recently, contributions that in addition to timing determine the optimal size of the investment have also appeared. Huberts et al. (2015) provide an overview of these contributions . The survey consists of two parts. First, single firm models are presented, and second, the authors give an overview of oligopoly models. As a general result, it is obtained that more uncertainty results in larger investment taking place at a later point in time. Since we assume our firm is a price taker we focus on the single firm models.

The real options literature distinguishes between discrete and continuous capacity choices. Dangl (1999) studies continuous capacity choice under uncertain demand. Examples of a papers that applies his approach are Fleten et al. (2007), Boomsma et al. (2012) and Bøckman et al. (2008). Fleten et al. (2007) study optimal capacity and timing of investment in decentralised renewable power generation. Boomsma et al. (2012) analyse investment timing and capacity choice for renewable energy projects under different support schemes. Bøckman et al. (2008) examine investment timing and capacity choice for small hydropower plants under uncertain electricity prices. Dias et al. (2004) and Décamps et al. (2006) consider the choice between several discrete capacities. They show that when an investor can choose between several different capacities he tends to wait longer to see which of the capacity choices will turn out to be optimal. An implication of discrete capacity choices is that the investment decision rule cannot be expressed in terms of a unique trigger level. Instead, there will be different capacities for different intervals of the uncertain state variable.

In this thesis, we consider a discrete capacity problem since the investor can only invest in an integer number of electrolysers. We seek to derive both the optimal timing and capacity choice along the lines of Dias et al. (2004) and Décamps et al. (2006). As a result, we derive the optimal capacity in which to invest for different intervals of the uncertain state variable. In contrast to these authors, we also seek to find the optimal operations of the plant and derive a solution using the LSM method.

Note also that works that deal with incremental investments have also been studied in the literature (e.g. Pindyck (1988)). However, this type of flexibility will not be considered here.

4.2.3 Flexible timing and capacity under operational flexibility

In general, there are few contributions studying both flexible timing and capacity under operational flexibility. Chronopoulos et al. (2013) extend the traditional real options approach by allowing for discretion over capacity while incorporating risk aversion and operational flexibility in the form of suspension and resumption options. They consider one underlying risk factor, namely revenue uncertainty. The model developed by Dangl (1999), also allow for operational flexibility. While the capacity is fixed as an upper boundary to the output, the output can be adjusted according to an uncertain demand. He finds that a higher uncertainty in future demand leads to an increase in optimal installed capacity. However, it causes the investment to be delayed longer. Hagspiel et al. (2016) elaborate on the paper by Dangl (1999) by analysing the specific implications of volume flexibility on investment timing and size. To do so they compare the optimal investment strategy for a flexible and inflexible firm. The flexible firm can costlessly adjust production over time with the capacity as the upper bound. The inflexible firm fixes production at capacity level from the moment of investment onwards. They find that the flexible firm is more valuable and invests in a larger capacity than the inflexible firm. Moreover, similar to Dangl (1999), Hagspiel et al. (2016) find that the firm tends to invest later in a larger capacity when the uncertainty in future demand is large.

4.2.4 Multi-factor modelling

While we do not consider multiple risk factors in this thesis, we have developed a flexible model that can possibly account for up to three risk factors. Having multiple risk factors makes it hard to derive a closed-form expression for the valuation PDEs. When there are multiple risk factors the Monte Carlo method is the most popular approach due to its simplicity compared to other alternatives Longstaff & Schwartz (2001). Its applicability to general real options problems has been analysed by Alesii (Forthcoming), Cortazar et al. (2008) and Schwartz (1997). They compare the LSM to other methods and conclude that that the LSM approach may be successfully applied for general real options problems.

Our contribution to the existing real options literature is twofold: (1) We study the combined problem of determining optimal timing, operations and capacity using the LSM that can account for up to three risk factors and (2) We examine the potential of real options valuation in hydrogen production from wind energy.

Our contribution to the existing real options literature is twofold: (1) We study the combined problem of determining optimal timing, operations and capacity using the LSM and a three-factor model and (2) We examine the potential of real options valuation in hydrogen production from wind energy.

Chapter 5

Model description

In this section we develop the model for finding the optimal plant operations and the optimal timing and capacity of the investment.

We consider the following investment opportunity: At any time τ, the firm can pay an investment cost, $I(Q)$, to install a hydrogen plant with maximum capacity of Q electrolysers with direct access to power from a local wind farm. We assume that the time from the investment decision is undertaken until the plant starts to operate is negligible. After the project is installed, the capacity presents an upper boundary for the output of the plant. The firm determines optimal investment timing and capacity at the same time under conditions of irreversible investment expenditures and an uncertain project value, $V(\tau)$. We assume that the lifetime of the hydrogen plant is L years and that the option to invest is available for M years.

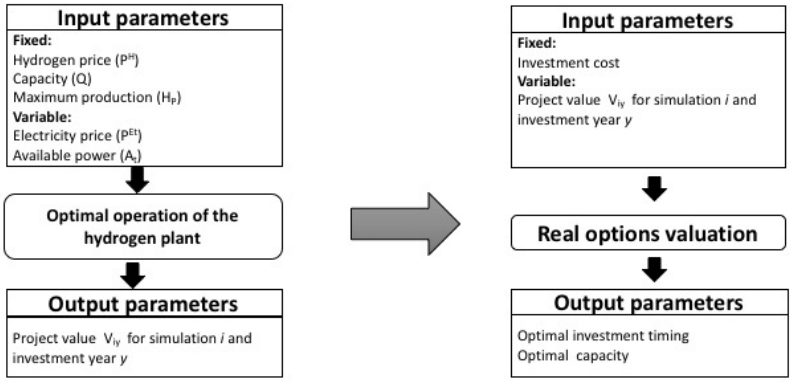
Once the investment is undertaken, the firm is concerned with operating the hydrogen plant such that its value is maximised. We assume that the firm is a price taker and that revenues are generated from selling hydrogen. The output is constrained by the maximum capacity and the available power from the wind farm. The plant can be operated in a flexible manner and at any point in time, the owner can either choose to produce hydrogen or suspend the operations of the plant. When the plant is operating, the owner receives the net cash flow from producing and selling hydrogen. In a suspended state, no cash flows are received. We assume that there no costs of switching between the two states and that the plant operations can be instantly started or suspended. Given this flexibility, we develop a model to determine how to operate the plant in order to maximise its value.

The main risk factors motivating a real options approach are uncertain electricity prices, uncertain hydrogen prices and uncertain amounts of available power. All of these risk factors give rise to an uncertain project value. The electricity price accounts almost for all the variable cost of production from electrolysis [18] and the hydrogen price and available power accounts for the revenue generated by the plant. However, in the case study in Chapter 7, we will assume that electricity price is the only underlying risk factor. Due to limited information available, we assume that the hydrogen price is deterministic and for simplicity we assume that the available power follows the average historical production. The model we develop in this section will therefore be formulated assuming that electricity price is the only risk factor. To model the electricity price, we simulate 10,000 future price paths that serve as input to the model. However, we emphasise that the model can easily be adjusted to account for multiple risk factors by simulating the other two risk factors in a similar way. The general model therefore does not make any assumptions about these underlying risk factors. They can follow any processes and be correlated with each other. This flexibility is one of the advantages of using a LSM.

As illustrated in Figure 5.1, the model we develop consists of two parts: (1) an optimisation model to find the optimal operation strategy that maximises the value of the plant and (2) a real options valuation to find the optimal timing and capacity of the investment. Several operational and cost parameters in addition to 10,000 simulated electricity price paths, hydrogen price and available power serve as input to the optimisation model in the first part. For each simulation i of the electricity price and year y, $y \in [0, 1, ..., M]$, the optimisation model finds the maximum value of the project, which we denote by $V(Q)_{iy}$. The process is repeated 10,000 times for each path i and year y. The result is then 10,000 Monte Carlo simulations of the project value for each year over the lifetime of the option, $y = 0$ to $y = M$. Output from the optimisation model for different capacities in addition to the investment cost serve as input to the real options valuation in the third part. The output of the real options model is the value and the optimal capacity and timing of the investment.

[18] Körner (2015) uses electricity price together with investment cost to calculate the levelised cost of production. Similar to Körner (2015) we therefore assume that electricity price is the only variable cost of production.

Figure 5.1: Model parts



5.1 Optimal operation of the hydrogen plant

The optimisation model we develop here optimises operation of the hydrogen plant in order to maximise the value of the firm.

In the problem studied in this thesis, the firm receives a cash flow every hour from the corresponding operating mode of the hydrogen plant. Each hour, h, the firm can choose between one of two modes: operating or suspended. Since the firm is a price taker and has a fixed production capacity, the optimal production strategy constitutes to produce hydrogen when revenues are larger than variable costs. From the investor's perspective, the opportunity cost of producing hydrogen is the money lost from not selling the electricity in the market. This means that the firm has to include the electricity price as a variable cost of hydrogen production. Hence, every hour, the optimal strategy constitutes comparing the variable cost of production to the price from selling hydrogen. If the hydrogen price is higher than variable costs, the optimal decision is to produce hydrogen. The optimal decision is independent of the amount of wind power available.

We formulate the following linear programming problem that maximises the annual cash flows from the hydrogen plant:

$$\text{maximise} \sum_{t=1}^{T} P^H \eta_E x_t - \sum_{t=1}^{T} P_t^E x_t - \sum_{t=1}^{T} x_t \eta_E C - \sum_{t=1}^{T} P_t^E l_t \tag{5.1.1}$$

$$\text{subject to} \qquad x_t \leq QK, \qquad \forall t \in T \tag{5.1.2}$$

$$x_t \eta_E \eta_L \leq l_t, \qquad \forall t \in T \tag{5.1.3}$$

$$x_t + l_t \leq A_t, \qquad \forall t \in T \tag{5.1.4}$$

Variables and parameters in the model are summarised in Table 5.1. The variable inputs to the optimisation model are electricity price, P_t^E, and available power, A_t for the year y which we want to find the annual cash flow. The fixed inputs are hydrogen price, P^H, efficiency of the electrolyser, η_E, number of electrolysers, Q, transportation cost, C, efficiency of liquefaction, η_L, and maximum production, K. The decision variables of the model are power consumed by the electrolyser, x_t, and power consumed by the liquefier l_t.

The objective function, equation (5.1.1), consists of four terms. The first term denote the total annual revenue from production. The second term denotes the variable cost due to the electrolyser. The third term is the variable cost of liquefying the hydrogen. The last term denotes the variable cost of transporting the hydrogen.

The objective function is subject to several constraints. The first constraint, equation (5.1.2), states that the maximum production must be less than the capacity of the plant. The second constraint, equation (5.1.4), states that the sum of the power used by the electrolyser and liquefier must be less than the available power. The third constraint, equation 5.1.3, states that all of the hydrogen produced must be liquefied.

The output of the linear program is the annual cash flow for year y which we denote C_y. However to value the hydrogen plant for the M year period, we need to know how the cash flows from all the possible years of operation, i.e. from $y = 0$ to $y = L + M$. For each electricity price path, the linear program is therefore run $L + M$ times for $y = 0$ to $y = L + M$. Recall that since we assume that Q cannot be changed once the hydrogen plant has been built we keep Q constant for all the

Table 5.1: Parameters and variables used in the optimisation model

Symbols	**Explanation**	**Unit**
P^H	Hydrogen price	€/kg
P_t^E	Electricity price at time t	€/MWh
x_t	Power consumed at time t, ≥ 0	MWh
η_E	Efficiency of conversion from power to hydrogen	kg/MWh
C	Transport and compression cost	€/kg
Q	Number of electrolysers	-
K	Maximum production	MWh
A_t	Available power at time t	MWh
l_t	Power drawn to liquefaction	MWh
η_L	Efficiency of liquefaction	MWh/kg

years. For a given Q the output is then a $1 \times [L + M]$ vector with all the potential cash flows the project can generate.

Given the 10,000 Monte Carlo simulations of the electricity price, we repeat the process described above for all the paths. The output is a $10,000 \times [L+M]$ matrix with cash flows for all possible years of operation. We denote the cash flows C_{iy}, where y refers to the year of operation and i refers to the input electricity price path.

With the yearly cash flows over the lifetime of the project we can calculate the present value of investing in the hydrogen plant in year y given a discount rate r:

$$V(Q)_y = \sum_{l=y}^{L} \frac{C_l}{(1+r)^{l-y}} \tag{5.1.5}$$

where $V(Q)_y$, is the value of the project with capacity Q in year y. Note here that $V(\tau)$ has been discretised to annual project value, $V(Q)_y$, in order to calculate the value of the project using the output from the linear program. By changing the input parameter Q, the maximum project value can be found for different capacities.

Given the 10,000 Monte Carlo simulations we denote value of the hydrogen plant in year y for path i, $V(Q)_{yi}$.

5.2 Real options valuation

We are considering the following investment opportunity: At any time τ, the firm can pay an investment cost, $I(Q)$ to buy a hydrogen plant with capacity Q. After the project is installed with a maximum capacity Q, this capacity represents an upper boundary to the output quantity. The firm has to determine optimal investment timing and optimal capacity choice at the same time under conditions of irreversible investment expenditures and an uncertain future project value, $V(\tau)$. By postponing the investment, the firm can obtain more information about the uncertain cash flows to inform the capacity decision. In continuous time, this can be formulated as an optimal stopping problem:

$$F(\tau) = \max_{0<\tau<T,Q} \mathbb{E}[(V(\tau,Q) - I(Q))e^{-\rho\tau}] \tag{5.2.1}$$

where $F(\tau)$ is the value of the option, τ is the optimal stopping time, T is the lifetime of the option, Q is the capacity, $V(\tau,Q)$ is the value of the project and $I(Q)$ is the investment cost.

In order to reduce the complexity of this problem we will assume that the option holder can only invest once a year during the lifetime of the option and not at any time τ. By discretising the problem this way, we can value the investment opportunity as a Bermudan option. A Bermudan option allows the owner to exercise the option between a number of given discrete times during the lifetime of the option. Valuing the investment opportunity like this also resembles real life business processes, where investment decisions are typically made yearly and not in continuous time.

5.2.1 Value of the option to invest

We approximate the value of the Bermudan option by simulation using the LSM described by Longstaff & Schwartz (2001). In short terms, it enables the use of Monte Carlo simulations for unbiased value approximations by avoiding perfect foresight. This algorithm utilises concepts behind options pricing and we briefly explain how LSM works here. For a more detailed explanation, please see Appendix A.

The decision to exercise the Bermuda option is based on comparing the value of exercising now with the value of keeping the option alive for one more period when a similar choice can be made. Here, exercising corresponds to making the investment and continuation corresponds to waiting. Letting $V(Q)_y - I(Q)$ denote the exercise payoff, the optimal choice can be described by the Bellman equation:

$$F_y = \max(V(Q)_y - I(Q), \frac{1}{1+\rho}\mathbb{E}_y[F_{y+1}] \tag{5.2.2}$$

Hence, it is optimal to exercise an option when the payoff from immediate exercise is higher than the expected payoff from continuation. The value of exercising is known to the option holder, but the continuation value $\mathbb{E}_y[F_{y+1}]$, is random from the perspective of period y and is conditioned on the knowledge we have in the current period. When the problem has a fixed finite time horizon T, we know the continuation value at time T and we can solve the problem by working backwards. The main idea of the LSM method is to approximate these continuation values by regressing the next period continuation values on the current values of the explanatory variables.

The inputs for the LSM valuation is one exogenous variable: the payoff from exercising, $V(Q)_{iy}$. This value exists for each of the 10,000 unique paths i and each possible year y the investment can be undertaken. Using the valuation framework described above, the optimal exercised strategy for each time step and all the simulated paths is given by:

$$F_{iy} = \max(V(Q^*)_{iy} - I(Q^*), \frac{1}{1+\rho}\mathbb{E}_y[F_{iy}] \tag{5.2.3}$$

At each time y, the value of exercising $V(Q)_{iy} - I(Q^*)$ is known to the investor, because $V(Q)_{iy}$ can be calculated from equation 5.1.5. The optimal investment capacity, Q^* is found by maximising the NPV of immediate exercise, $V(Q)_{iy} - I(Q)$, with respect to Q. This occurs when the marginal value of an extra unit of production capacity equals its marginal cost. However, in our model the capacities are discrete. In the implementation of hour model, we therefore systematically increase Q to find the value that maximises $V(Q)_{iy} - I(Q)$.

Knowing the value of immediate exercise, the key to determine the maximum value of Equation 5.2.3 is therefore to identify the conditional expected value of continuation, $\mathbb{E}_y[F_{y+1}]$. According to Longstaff & Schwartz (2001) the conditional expectation function can be estimated from the cross-sectional information in the simulated paths using least squares. At each time y, the LSM algorithm regresses the next period, $y + 1$, simulated continuation values on functions of the current values of the explanatory state variable $V(Q)_y$. The fitted value from this regression provides a direct estimate of the conditional expectation function at time y.

The main advantage of using LSM is that it can be readily applied when the value of the option depend on multiple underlying uncertainties. When the option depends on multiple underlying factors analytical and tree solutions often become intractable. As we have explained before, this means that uncertain hydrogen price and available power can be taken into account by the model. Moreover another major advantages is that it can be used to options whose underlying state variables values can be driven by a variety of stochastic processes (Longstaff & Schwartz, 2001).

Chapter 6

Model parametrisation

In this chapter we determine the values of the parameters used for the case study of an investment in hydrogen generation from wind power. The case study considered is a real wind farm, Valsneset, in Bjugn municipality in Norway. We assume that the lifetime of the hydrogen plant is 20 years, $L = 20$, and that the option to invest lasts for 10 years, $M = 10$.

We determine the parameters related to available power, investment cost, electricity price, transportation costs, efficiency of the electrolyser, efficiency of the liquefier, the discount rate, maximum production and hydrogen price. The results of the case study are presented in the next chapter together with a comparative statics analysis.

6.1 Available power, A_t

In the case study, Valsneset wind farm is the designated wind farm where hydrogen will be produced. The wind farm has five wind turbines with an effect of 2.3 MW each, giving a maximum effect of 11.5 MW. [19]

The power production from the wind farm is varying depending on weather conditions. We determine A_t based on a data set provided by our industry partner.

[19] The wind farm specifications can be found at: `https://tronderenergi.no/produksjon/kraftverk/valsneset`.

The data set comprises of hourly production data for the last six years. Since we have hourly data, we make a simplifying assumption that the power (MW) is constant during the whole hour of production. Moreover, we assume that the future production is deterministic and can be estimated from historical data, using the following equation:

$$A_t = \frac{1}{Years} \sum_{y=1}^{Years} s_{yt} \qquad \forall t \in T, \tag{6.1.1}$$

where A_t is the available power parameter used in the case study and s_{yt} is the hourly historical production. Note, since we assume a deterministic process we assume that available power is not correlated to the electricity price. For a stand-alone system, this assumption is considered to be correct (Aronsen, 2016).

6.2 Investment costs, $I(Q)$

The total investment cost of the hydrogen plant is given by,

$$I\left(Q\right) = \left(1 + \xi\right) \cdot \left[I_E(Q) + I_S\left(Q\right) + I_L\left(Q\right) + I_B(Q)\right] \tag{6.2.1}$$

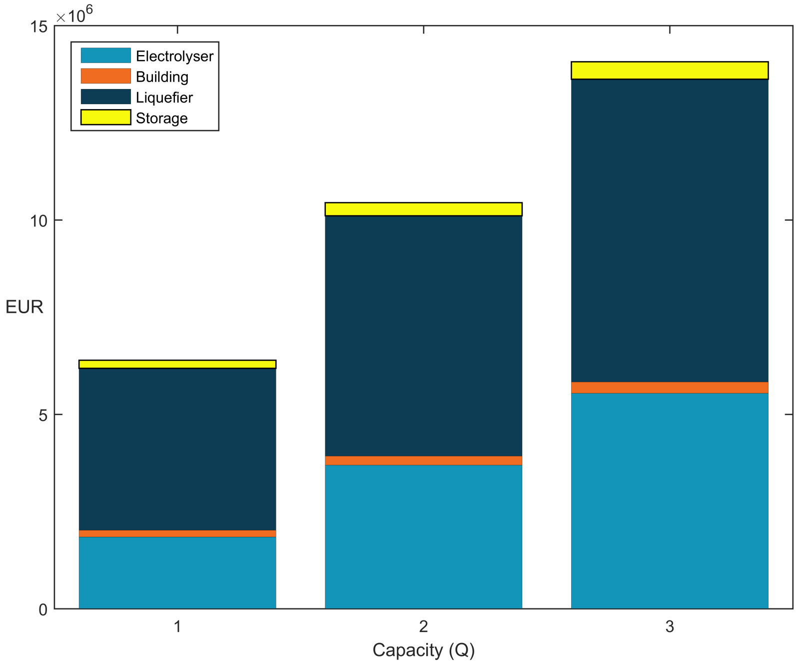
where ξ is the installations cost as a percentage of the whole investment cost, $I_E(Q)$ is the investment cost of Q electrolysers, $I_S(Q)$ is the investment cost of storage tanks as a function of Q, $I_L(Q)$ is the investment cost of the liquefier as a function of Q and $I_B(Q)$ is the cost of the building as a function of Q. In the following we describe the components of the investment costs in more detail. Figure 6.1 shows each component's share of the total investment cost for different capacities Q.

Investment cost of electrolyser, $I_E(Q)$

From the discussion about different available technologies in Section 2.3, alkaline electrolysers were described as the most mature technology. Here, we assume that the investor is considering to install commercial alkaline NEL-485 electrolysers, each with a capacity of 2.3 MW. The investment cost of an electrolyser is set equal to $I_E(1) = €\,1,340,000$.[20] Its specifications are shown in Table 6.1.

[20] The investment cost of a NEL-485 electrolyser was found in Løland (2015).

Figure 6.1: Investment cost of hydrogen plant for different capacities Q



The cell stacks must be replaced every 7 years (Løland, 2015). In the case study we assume that the lifetime of the hydrogen plant is 20 years and as a result the electrolyser needs to be renewed 2 times during the time period considered. We assume that one regeneration costs 20 % of the initial investment cost. Two regenerations therefore costs 40% of the initial investment cost. The total investment cost for Q electrolysers, including regeneration, is therefore $I_E(Q) = 1.4 \cdot I_E(Q)$.

Table 6.1: NEL-485 specifications

Technical specification	**Value(s)**
Dynamic capacity range (Nm^3 H_2/hr)	97 - 485
Power consumption (kWh/Nm^3 H_2)	4.4
H_2 purity (%)	99.9 ± 0.1

Investment cost of storage, $I_S(Q)$

Due to the relatively large production capacity of one electrolyser we assume that liquid storage is required. One NEL-485 electrolyser can produce a maximum of F = 891kg of hydrogen each day. Hence, if we were to use gas storage it needs to be transported more than once a day since a gaseous truck transport has capacities between 300 kg and 600 kg. Based on the location of the hydrogen plant at Valsneset, it will not be economically sensible to transport hydrogen many times a day. Thus, in our case our calculations will be based on using liquid as the storage medium.

According to Yang & Ogden (2007), the size of liquid storage needs to be 200% of the daily hydrogen flow. According to Løland (2015) the investment cost is given by:

$$I_S(Q) = I_{0S}\left(2 \cdot \frac{Q \cdot F}{300,000}\right)^{0.7}, \tag{6.2.2}$$

where I_{0S} = €8.36 million and F is the maximum production of one NEL-485 electrolyser in kg per day. From equation 6.2.2 we observe that there are great economies of scale.

Investment cost of liquefaction, $I_L(Q)$

Since the hydrogen is stored as a liquid, it needs to be liquefied. According to Yang & Ogden (2007) the investment cost of the liquefier is given by:

$$I_L(Q) = I_{0L}\left(\frac{Q \cdot F}{30,000}\right)^{0.57} \tag{6.2.3}$$

where I_{0L} = €29,220,000 and F is the maximum production of one NEL-485 electrolyser in kg per day. We see that the investment cost of the liquefier is also subject to economies of scale[21].

Building costs, $I_B(Q)$

Based on estimates by our industry partner we have assumed that the building cost of the plant will depend on the number of electrolysers we invest in. Further, there is a base cost of housing the liquefier, as well as economies of scale on the number of electrolysers installed. The cost is estimated to be:

$$I_B(Q) = €52,950 \cdot Q + €105,900 \tag{6.2.4}$$

[21] Average exchange rate for 2007 from `https://www.oanda.com/currency/average`.

Installation costs, ξ
Installation costs are not included in the previous stated costs. We estimate that the costs of installing the electrolyser, liquefier, storage and building are a percentage of their capital costs. Further, we assume that the installation costs will amount to 10%, so $\xi = 10\%$.

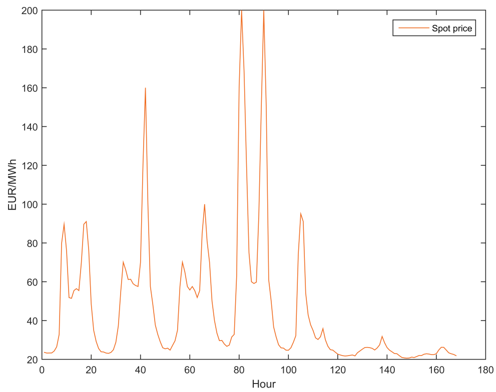
Decline in investment cost per year, ζ
We assume that the investment costs described above decline every year due to efficiency improvements and technological developments. For example, Bertuccioli et al. (2014) estimate the investment cost of alkaline electrolyser to decrease by about 3% annually. We assume $\zeta = 0.95$, thus a decrease of 5% per year. We assume a higher decline in investment cost due to for example larger expected cost reductions for liquefiers (Møller-Holst, 2016).

6.3 Electricity price, P_t^E

In this subsection, we develop a forecast for electricity prices. As already explained we consider the day-ahead spot market.

Historical spot prices for the Nord Pool power market are available for the period 2013-2016. A subsample of the historical system prices are illustrated in Figure 6.2 for week 3, 2016. Electricity spot price exhibits mean-reversion, high and clustered volatility, price spikes and seasonal patterns (Weron, 2014). While mean-reversion is a common feature of commodity prices, the other features arise from two distinct characteristics of electricity. First, the high volatility and price spikes arise because electricity cannot be stored on a large scale and hence the supply and demand needs to be balanced at every point in time. The price spikes are usually explained by a sudden increase in demand and/or supply for example due to unpredicted changes of weather conditions. Positive spikes occur when the demand reaches the limit of available supply. Negative spikes may occur in periods of low demand and/or excess supply. Second, the seasonality can mainly be explained by the varying demand curve for electricity. It varies during the year due to changing weather conditions and throughout the week and day due to the business cycle. In the future, the supply is also expected to show stronger seasonal effects due to the growing proportion of weather dependent renewable energy sources (RES) in the energy mix.

Figure 6.2: Spot price Nord Pool, week 3, 2016



Source: Nord Pool (2016)

A variety of methods and ideas have been tried for electricity price forecasting over the last 15 years, with varying degrees of success (Weron, 2014). Weron (2014) describes five main categories: Multi-agent, fundamental, reduced-form, statistical and computational intelligence. The models described mainly differ in terms of the forecasting approach applied and the forecasting horizons considered. In this thesis, we are interested in models with long forecasting horizons since we model the operations of the plant for 30 years. An implication of the relatively long forecasting period is that the equilibrium level to which the spot price reverts to is not constant. Schwartz & Smith (2000) describes this concept for commodities and introduces a distinction between mean-reversion in the short-term and the equilibrium level to which prices revert in the long-term. Schwartz & Smith (2000) argue that the long-term equilibrium price evolves over time reflecting expectations of the exhaustion of existing supply, improving technology for the production, inflation as well as political and regulatory effects. The long-term equilibrium is modelled as a Brownian motion process. They argue that short-term deviations may reflect, for example, the short-term changes in demand resulting from variations in the weather or intermittent supply disruptions described above. The short-term deviations in the spot price can therefore be defined as the difference between spot and equilibrium process and are expected to revert towards zero following an Ornstein-Uhlenbeck process. In addition to the short-term mean-reversion and the long-term equilibrium level prices, seasonality can be incorporated by including time-dependent constants (Schwartz & Smith, 2000). Based on this, the spot price can be decomposed into three main components: (1) a long-term equilibrium level to which the prices revert, (2) a short-term mean-reverting stochastic component and (3) a seasonal component. For electricity prices the seasonal component can be further decomposed into a short term seasonal component (STSC) and a long-term seasonal component (LTSC) (Weron, 2014). These short-term and long-term dynamics must therefore be taken into account in the choice of forecasting model.

In the real options literature reduced-form models are often used to forecast long-term prices. These models are based on the one- or two factor mean-reverting processes for commodity prices developed by Schwartz & Smith (2000). One advantage of these models is that they take into account the long-term equilibrium level and the long-term and short-term seasonality described above. Furthermore, to reflect the specific short-term stochastic component of the electricity price, jump-diffusion and Markov regime-switching models have been proposed (Weron, 2014). These models better capture spikes and clustered volatility compared to the Ornstein-Uhlenbeck process used in the model developed by Schwartz & Smith (2000). These reduced form models lie at the heart of derivative pricing and often allow for analytic derivative pricing formulas (Weron, 2014). A drawback of using these models is that we have to assume that the electricity price follow a well-defined stochastic processes. However, it is not clear what the correct stochastic processes is. Moreover, once a process is chosen, the parameters of these models either must be arbitrarily set or calibrated on for example historical data. In some way or another few parameters needs to capture potentially complex and various expectations about the future.

In collaboration with our industry partner we have chosen to use the EFI's Multi-area Power-market Simulator (EMPS) to forecast long term prices. EMPS is a tool for forecasting and planning in electricity markets and is used by most large actors in the Nordic market to forecast long-term prices (SINTEF, 2016). Note that for short-term forecasting companies usually develop their own models that they keep as a company secret (Aronsen, 2016). The model is designed for electricity markets with a considerable share of hydropower and is developed by SINTEF, a Scandinavia based non-profit independent research organisation expertise in many research areas. To forecast electricity prices, the model takes four main elements into account:

- Generation capacity of hydro, thermal, wind and solar power.

- Transmission constraints and grid expansions such as connections to new areas.
- Demand for electricity, which is affected by temperature and prices.
- Historical climate data for hydrology, temperature and wind.

The EMPS model consists of a strategy part and a simulation part. In the strategy part, a residual demand is specified for the hydropower, and this is the demand that needs to be matched by hydropower generation. Then stochastic dynamic programming is used to calculate the optimal supply (Smelvær, 2015). In terms of the categories described by Weron (2014) it can be considered as a hybrid multi-agent model, since it models several heterogeneous agents and simulates their interaction.

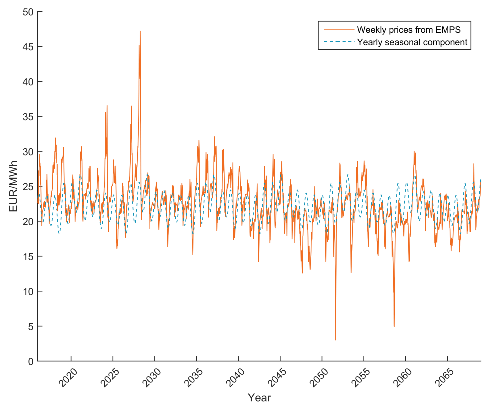
The output of the model is forecasted weekly electricity prices. The weekly price is defined as the average spot price during a week and can therefore also be understood as the equilibrium level to which the prices revert. The main advantage with the EMPS is that it takes into account future expectations about the power market such as generation capacity expansion, expansion of the grid and future demand. This is an important capability of the model since many changes are expected to affect the Nordic power market (Myhre, 2016). For example are Swedish stable nuclear power expected to be closed down and replaced by unreliable wind power. Moreover, sources such as coal are being phased out. A major advantage with the EMPS models is that it takes these anticipated changes into account. By using this model, we can therefore overcome the challenges of calibrating the parameters of the reduced-form models. A drawback of this model however is that the EMPS only captures the long-term dynamics and as a result, it does not capture short-term price dynamics.

As a result, we need an additional model capture the short-term dynamics of the price. To do this we use a reduced-form mean-reverting jump-diffusion model with equilibrium level equal to the weekly price found using the EMPS.

Long-term dynamics of the spot price

We use the EMPS to forecast weekly prices from 2015 to 2069. The model therefore takes into account our industry partner's expectations about the future power market. To forecast prices over this period the model uses historical weather data from 1958 to 2013. The assumption made by the EMPS is that this weather data is exactly replicated over the forecasting period from 2015 to 2069. In other words, it assumes that the weather in 2015 is exactly the same as in 1958 and so forth. This will almost certainly not be the case, but it is how the industry usually forecast prices (Aronsen, 2016). Figure 6.3 shows the forecasted price series from the EMPS.

Figure 6.3: Forecasted weekly prices from the EMPS



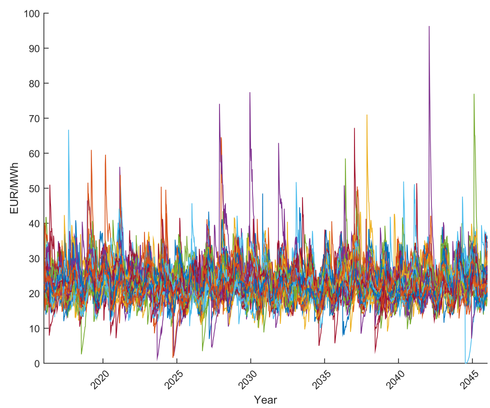
We would like to forecast electricity prices without assuming that the historical climate repeats itself over the forecasting period. We therefore introduce uncertainty to the development of future prices by fitting a stochastic process to the time series in Figure 6.3. To find an appropriate stochastic process we first take the natural logarithm of the data set and then test the time-series for a unit root using the Augmented Dickey-Fuller (ADF) test. The ADF test concludes that the data is stationary and therefore is characterised by mean-reversion. Another important characteristic that can be observed from Figure 6.3 is the seasonal patterns throughout the year. To capture these two characteristics we let the natural logarithm of the weekly price, $\ln(P_w^W)$ be a sum of a deterministic yearly seasonal component and a stochastic component: $\ln(P_w^W) = l_w + X_w$.

The deterministic yearly seasonal component, l_t, is referred to as LTCS of the electricity price (Weron, 2014). To capture the LTSC we fit a Fourier function to the data-set of weekly prices. To capture the stochastic component, X_w, we first deseasonalise the original time series by subtracting the fitted Fourier function from the weekly prices. We then fit the following first order auto regression, AR(1), to the deseasonalised data:

$$X_t = \alpha + \beta X_{w-1} + e_w \,, \quad e_w \; i.i.d.(0, \sigma^2) \tag{6.3.1}$$

where i.i.d means that the random variables are independent and identically distributed. The independence assumption implies that there is no auto correlation in the process and the identical distribution implies that the random variables all have the same distribution parameters. In particular, the variance is the same at all points in time. The AR(1) model is in fact the discrete time version of the mean-reverting Ornstein-Uhlenbeck (Alexander, 2008).

Figure 6.4: Weekly simulated prices



The parameters in equation 6.3.1 can be found using regression, which gives $\alpha \approx 0$ and $\beta = 0.922$. To find the probability distribution of e_w, we use the probability distribution fitting application in MATLAB. Of all the available distribution in the application, the residuals fit a t location-scale distribution best. This distribution is useful for modeling data distributions with heavier tails (more prone to outliers) than the normal distribution. The fitted distribution has mean and variance of €22.8/MWh and €10.3/MWh, respectively. We simulate 10,000 paths, and show 100 of them in Figure 6.4. As already explained, these prices represent the equilibrium the price revert to during a week.

Short-term dynamics of the spot price

Knowing the long-term price dynamics, next we need to model the short-term price dynamics. The short-term dynamics have already been shown in Figure 6.2, and the prices exhibit mean-reversion, high and clustered volatility, price spikes and seasonal patterns. Our industry partner believes that the short-term dynamics are going to change in the future. Their view is supported among others such as Myhre (2016), who is power trading manager in LOS Energy. Due to the increased proportion of RES in the energy mix, Myhre (2016) expects the future short-term dynamics to be different. For example, he expects price spikes to become more frequent and hence that the volatility will increase. He argues that there is often little wind on cold days and this might create a shortage in supply leading to price spikes. However, these price spikes are highly randomised events and hard to predict.

To model this short-term behaviour, we let the short-term natural logarithm of the hourly price $\ln(P_h^H)$ be a sum of a deterministic weekly and daily seasonal component and a stochastic component: $\ln(P_h^H) = s_h + Y_h$. With respect to seasonality recall that we have already estimated the long-term seasonal component into account. Hence, we only need to consider the short-term seasonal component here.

We assume that s_h can be modelled using a Fourier function, and that the short-term deviations,Y_h, revert toward zero following an Ornstein-Uhlenbeck process with jumps. In continuous time this process is formulated as:

$$dY_t = -\kappa Y_t dt + \sigma dZ_t + J(\mu_J, \sigma_J)Poisson(\lambda) \tag{6.3.2}$$

The parameter κ denotes the speed of mean-reversion parameters. The parameter σ is the volatility and Z_t is the standard increment of a Brownian motion. The jump size is $J(\mu_J, \sigma_J)$, with normally distributed mean μ_J and standard deviation σ_J. The Poisson process $Poisson(\lambda)$ has jump intensity λ.

For the case study, we calibrate this process to model the short-term dynamics of the historical market price on Nord Pool Spot from Jan 2013 to May 2016. Table 6.2 shows the parameters that we have used for the short-term component of the price.

Table 6.2: Mean reversion parameters

Parameter	**Values**
σ	0.0615
σ_J	0.1011
μ_J	0.0336
κ	0.5
λ	0.0609

Forecasted electricity prices

With the two models for short and long-term price dynamics we forecast the hourly electricity price for 30 years or $52 \cdot 30 = 1,560$ weeks. To do this wee first need to define the relation between w and h, so that the weekly equilibrium level X_w and long-term seasonal component l_w can used to forecast hourly spot prices. We let the hourly equilibrium level be denoted by X_h and the hourly long-term seasonal component by l_h and define the following relation between w and h: $w = \lceil \frac{h}{168} \rceil$

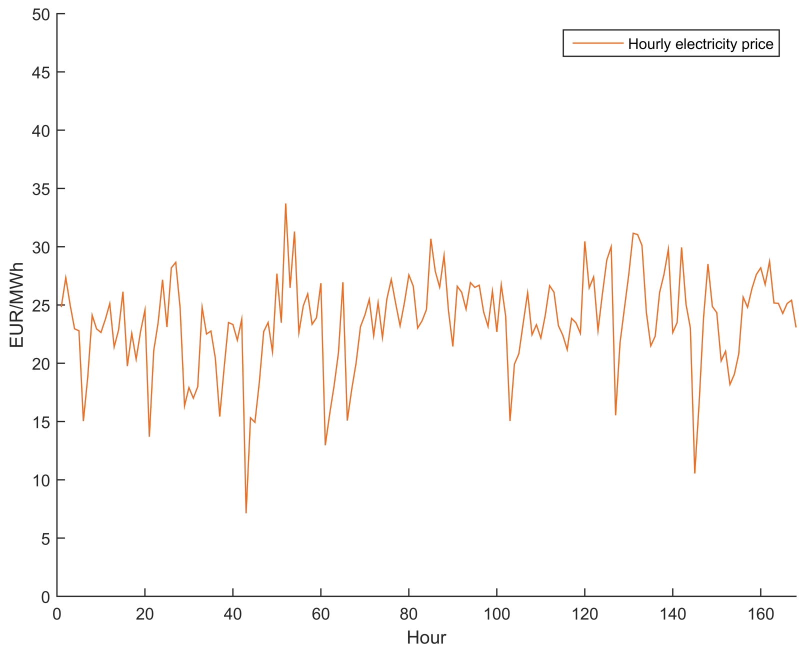
To forecast the spot price P_h we use the formula:

$$P_h = l_h + s_h + X_h + Y_h \tag{6.3.3}$$

which means that the hourly price is the sum of a long term seasonal component, a short term seasonal component, a long-term stochastic equilibrium level and a short term stochastic component. While in discrete time, this model is similar to the one developed by Schwartz & Smith (2000), where the long-term equilibrium and short-term dynamics are modelled as a sum of two processes. It will be mean-reverting towards the long-term equilibrium level with smaller deviations and price spikes in the short-term.

We set the initial price to be the average price for May 2016, $P_0^E =$ €23.17/MWh. The forecasted price process of week 8, 2017 is shown in Figure 6.5. The daily mean and volatility of the prices for the whole 30 year forecasting period are 22.68 and 4.82 (€/MWh), respectively.

Figure 6.5: Price path for medium volatility



Volatility σ = €3.7/MWh and simulated week 8 in 2017.

6.4 Transportation costs, C_T

We consulted an industry expert in transportation of gases to find an estimate for the cost of transporting liquid hydrogen per kg. Out of confidentiality reasons, we cannot print the exact number that we use in the model. Nevertheless, a rough estimate is a cost of €0.5-3/kg hydrogen for a distance of 250 km. Recall from Section 2.4 that the capacity of a liquid truck is up to 4,000 kg.

6.5 Efficiency of electrolyser, η_E

From calculations based on NEL Hydrogen (2015) we estimate the amount of kilogram produced per MWh (kg/MWh) from the NEL-485. The efficiency is given by

$$\eta = \frac{485 \cdot 0.08988}{2.3} = 18.95\,\mathrm{kg/MWh}, \tag{6.5.1}$$

where 485 Nm^3 is the maximum production of a NEL-485 for one hour, 0.08988 $\mathrm{kg/Nm}^3$ is the conversion rate for hydrogen[22] and 2.3 MW is the power drawn from the electrolyser.

6.6 Efficiency of liquefier, η_L

According to Stolzenburg & Mubbala (2013) the energy consumption of the liquefier is $\eta_L = 10$ kWh/kg.

6.7 Discount rate, r

The discount rate should reflect the risk embedded in the project, and is usually set by the company. This is considered to be company sensitive information. Out of confidentiality reasons we therefore do not print the discount rate used by the investor.

6.8 Maximum production, K

The maximum production of the NEL-485 electrolyser when operating is 43.6 kg/hour (100% load) at 2.3 MW.

6.9 Hydrogen price, P^H

In Section 3.4 we developed three price scenarios for the hydrogen price:

- Scenario 1: P^H =€8.8/kg
- Scenario 2: P^H =€6.1/kg
- Scenario 3: P^H =€4.4/kg

[22]The conversion rate of hydrogen was found at: `http://www.uigi.com/h2_conv.html`.

Chapter 7

Results

In the following chapter we first present the results of the case study of the investment in hydrogen production from wind power using the model from Chapter 5 and the parameters in Chapter 6. Second, we conduct a comparative statics analysis of the optimal timing and capacity.

The model presented in Chapter 5 was implemented in MATLAB. In order to solve the linear program of the optimisation model, MATLAB was set up in order to communicate with Xpress optimisation suite. Due to the complexity of the model and the number of simulated paths, the code was designed in order to take advantage of parallel computing. The running time of the model was approximately 1.5 hours using a 32 kernel processor.

7.1 Case study

In this subsection, we present both the result from the optimisation model and the output from the investment model. The models have been run for each of the three hydrogen price scenarios, P^H =€8.8/kg, P^H =€6.1/kg and P^H =€4.4/kg.

7.1.1 Scenario 1: P^H =€8.8/kg

The result of the investment model for scenario 1 is shown in Table 7.1. The optimal capacity found by the investment model was $Q = 2$ electrolysers, and an option value of €15.1 million. Moreover it is optimal to invest immediately. The output of the optimisation model is illustrated in Figure 7.1. The figure shows the distribution of the maximised project values, V_y, for each possible year of investment. It can be observed that the mean and variance of the distributions are approximately the same. As result the project value is not expected to grow or decrease significantly over the lifetime of the option. This explains why it is optimal to invest immediately. By waiting the investor faces a trade-off between foregoing current profit with the benefit of paying a lower investment cost in the future. However, since the value of the project is not expected to grow significantly there is limited value to waiting for potential higher profits. Moreover, future cash flows are discounted more if investment happens later. In this scenario it is therefore optimal to invest sooner and receive the project value rather than waiting for lower investment costs.

Table 7.1: Model results for the three hydrogen price scenarios

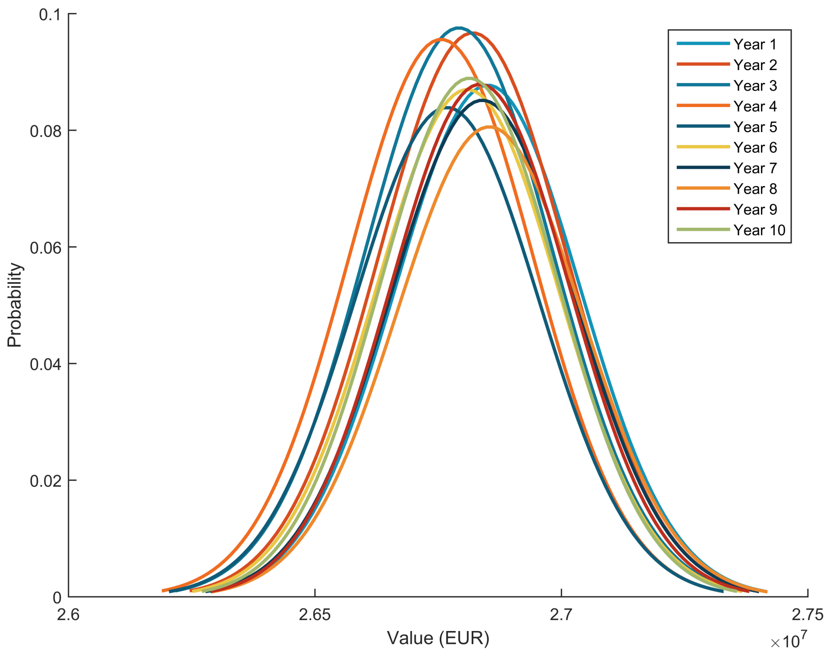
Scenarios	**Option value**	**Capacity**	**Investment time**	**Usage**	**Utilisation rate**	**H_2 produced per year (tons)**
P^H = €8.8/kg	€15.1M	2	Year 0	99.99%	62.6%	477
P^H = €6.1/kg	€3.16M	2	Year 10	99.92%	62.6%	476
P^H = €4.4/kg	€0	-	-	-	-	-

The details of the optimal operations found by the optimisation model is illustrated in Figure 7.2. The figure shows operations of the hydrogen plant in week 7 in year 13 after investment is undertaken for an example price path. The green line illustrates the profit from selling hydrogen per MWh and the orange line shows the variable costs per MWh during the week[23]. The total length of the bars shows the amount of available power from the wind farm. The two decision variables, power used to produce hydrogen and power used for liquefaction, is shown by the white and black part of the bar, respectively. The grey part of the bar indicates surplus power from the wind farm.

In Figure 7.2, the variable costs never exceed the hydrogen price. As a result, the operations of the plant are never suspended and the available power is therefore

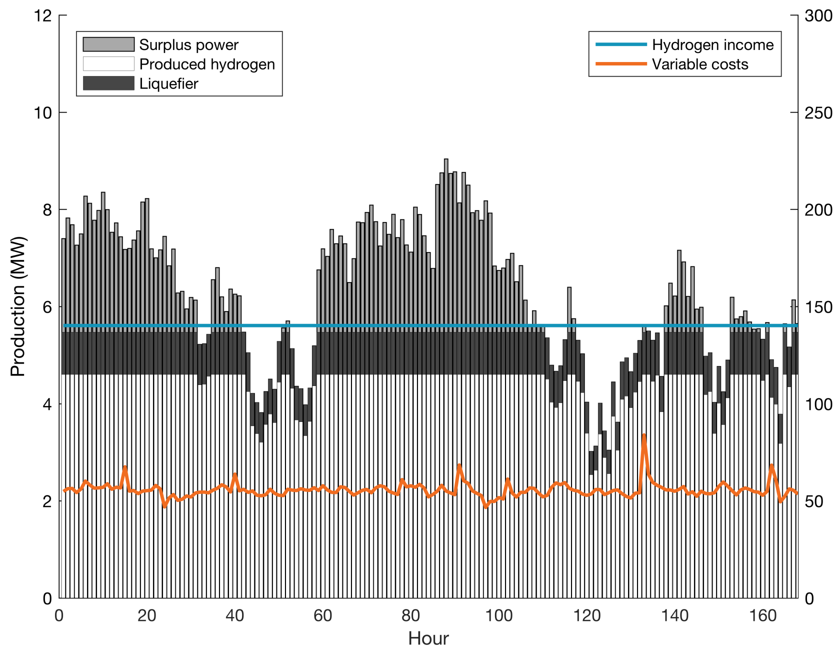
[23]The variable costs are the sum of electricity costs, due to the power consumption from the electrolyser and liquefier, and the transportation costs.

Figure 7.1: Distribution of present values of the hydrogen plant for each year during the lifetime of the option



The figure shows the distribution of the projects values for each year over the lifetime of the option. The distributions have similar mean and variance. This indicates that the project value is not expected to increase or decrease during the lifetime of the option.

Figure 7.2: Optimal operation of the hydrogen plant for scenario 1, $P^H = €8.8/kg$



Optimal operation of the plant for an example week is shown for scenario 1, $P^H = €8.8/kg$. The operations are never suspended during the week. The optimal capacity found by the investment model was 2 electrolysers, and the grey part of the bars indicates the capacity restricts the amount of available power used to produce hydrogen.

used to produce and liquefy hydrogen. However, a surplus of available power is indicated by the grey part of the bar. The surplus arises because more power is available from the wind farm than the electrolysers can use for production. With a capacity of two electrolysers we obtain a maximum power of 4.6 MW. If more power is available at a given hour it cannot be used to produce hydrogen.

Table 7.1 also shows the usage of the hydrogen plant as well as its utilisation rate[24] and the number of tons of hydrogen produced per year. We define the usage of the hydrogen plant as the average number of hours the plant is turned on during one year of operation. The usage is close to 100%, and hence its operations are rarely suspended. The flexible operations of the hydrogen plant therefore seem to have little value. The utilisation rate is 62.6%, which indicates that the available power

[24]Utilisation rate= $\frac{\text{Actual production}}{\text{Possible production(Q)}}$.

from the wind farm is not enough to operate the hydrogen plant at full capacity during the whole year. This means that the varying power supplied by the wind farm is the bottleneck for the utilisation rate.

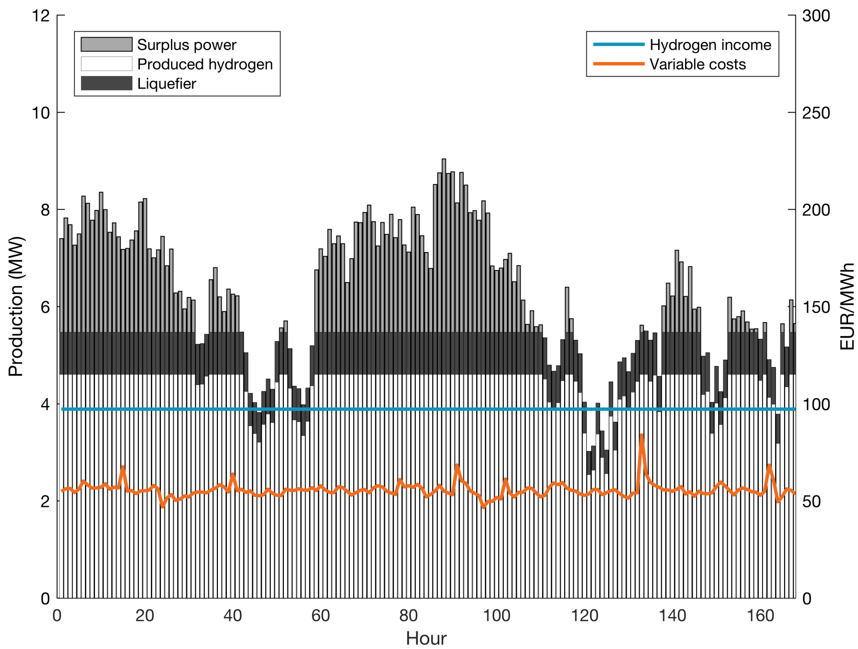
7.1.2 Scenario 2: P^H =€6.1/kg

The result of the investment model for scenario 2 is shown in Table 7.1. The optimal capacity found by the investment model was $Q = 2$ electrolysers, and an option value of €3.16 million. Moreover it is optimal to delay investment until the option expires in year 10. This indicates, that for the case with a hydrogen price of $P^H =$ €6.1/kg the profits foregone by waiting are smaller than the savings from waiting for a lower investment cost. Hence, it is optimal to wait.

Figure 7.3 illustrates the same week of operation, but for hydrogen price $P^H =$ €6.1/kg. The figure shows that while the hydrogen price and variable costs of production are closer to each other, the production is never suspended during the example week.

Table 7.1 also shows the usage of the hydrogen plant as well as its utilisation rate and the number of tons of hydrogen produced per year. Similar to scenario 1, the usage is close to 100% and its operations are rarely suspended. The flexible operations of the hydrogen plant therefore seem to have little value in this scenario as well. Similarly, the utilisation rate is 62.6%, which indicates that the available power from the wind farm is not enough to operate the wind farm at full capacity during the whole year.

Figure 7.3: Optimal operation of the hydrogen plant for Scenario 2, P^H =€6.1/kg



Optimal operation of the plant for an example week is shown for scenario 2, P^H =€6.1/kg. The operations are never suspended during the week. The optimal capacity found by the investment model was 2 electrolysers, and the grey part of the bars indicates the capacity restricts the amount of available power used to produce hydrogen.

7.1.3 Scenario 3: P^H =€4.4/kg

For scenario 3 the option value is zero and it is never optimal to invest. The reason why this is the case is that the project value is not expected to increase in the future. Hence, the value of the hydrogen plant will never become high enough to cover the investment cost during the lifetime of the option.

7.2 Comparative statics

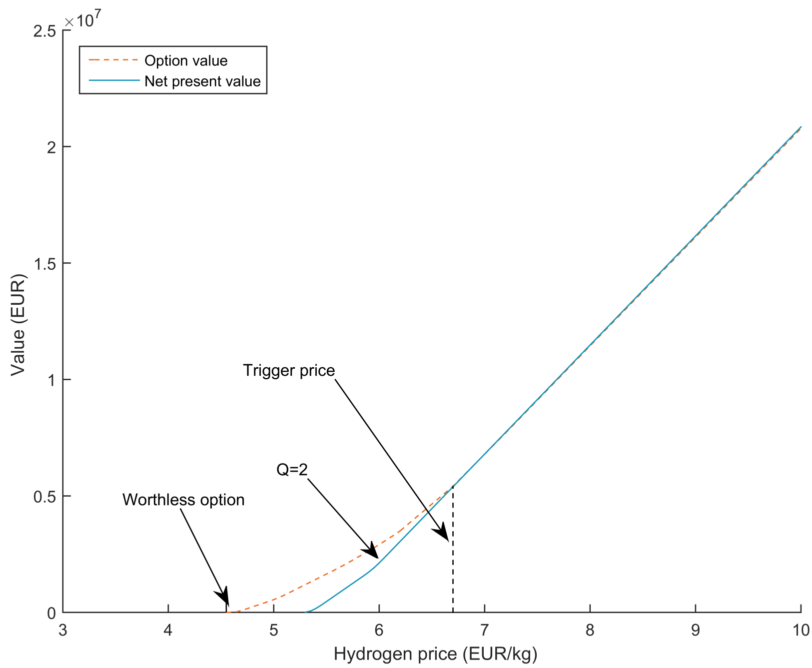
In this section, comparative statics is used to analyse how the optimal investment timing and capacity are affected by changes in the hydrogen price and the electricity price volatility. Note that the lack of analytical solution and running time of the code makes comparative statics analysis very complex. We have therefore focused on what the investor we consider thinks are the two most important uncertain factors.

7.2.1 Hydrogen price

Figure 7.4 shows both the option value and the NPV plotted against the hydrogen price. There are three price intervals of interest. First, when the hydrogen price is below $P^H =$€4.5/kg the option becomes worthless. As we have already explained, this happens because the value of the hydrogen plant never becomes high enough to cover the investment cost. Second, when the price is between $P^H =$€4.5/kg and $P^H =$€6.7/kg it is optimal to wait. By waiting the investor can benefit from a lower investment cost. For a price higher than $P^H =$€6.8/kg the investor is indifferent between waiting and investing. As a result the hydrogen price that triggers immediate investment is $P^H =$€6.8/kg.

Moreover the optimal capacity to invest in is different for different hydrogen prices. From the figure we observe that the investor never invests in a capacity of $Q = 1$. In contrast he invests in capacity of $Q = 2$ at the trigger level. While not shown in the figure, we find that the investor decides to invests in a capacity of $Q = 3$ electrolysers when the hydrogen price is larger than $P^H =$€15.2/kg. A higher hydrogen price gives higher cash flows and hence it becomes optimal to exploit all of the available power from the wind farm.

Figure 7.4: Real option value and NPV plotted against the hydrogen price

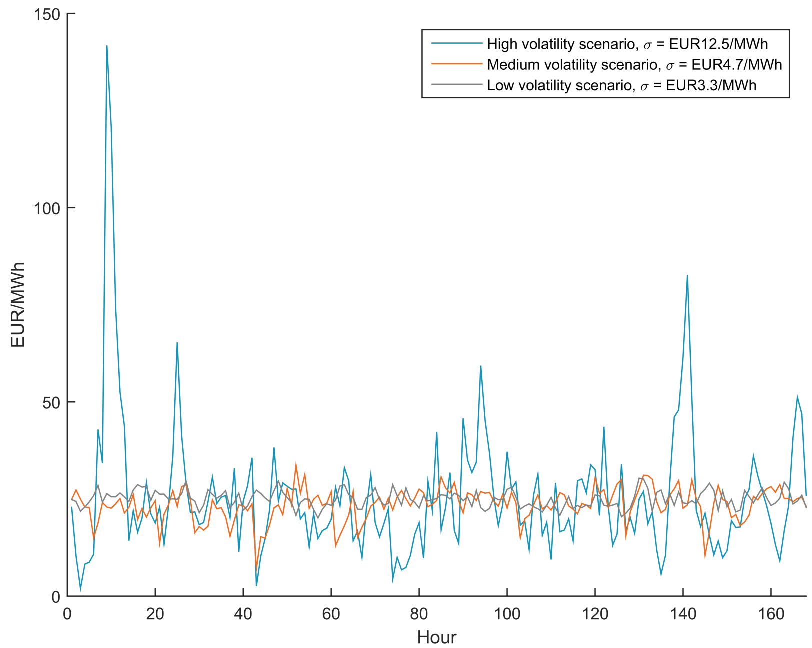


The figure shows the option value and NPV plotted against hydrogen price. For a hydrogen price below P^H =€4.5/kg it is never optimal to invest. For a price between P^H =€4.5/kg and P^H =€6.7/kg it is optimal to wait. For prices greater than P^H =€6.8/kg the investor is indifferent between waiting an investing. The optimal capacity at the trigger price is $Q = 2$, but increases to $Q = 3$ when the hydrogen price reaches €15.2/kg

7.2.2 Electricity price volatility

To illustrate the impact of electricity price volatility, we run the model with different price volatilities for the three hydrogen price scenarios. We develop three volatility scenarios: High, medium and low. The high volatility price process is calibrated to the most volatile week in the price data set from Nord Pool described in Chapter 6. The medium volatility price process is taken to be the same as the process used in the case study in the previous subsection. The low volatility price process is calibrated to the least volatile week in the price data set. We illustrate a one week sample path for the price processes with different volatilities in Figure 7.5. The absolute volatilities of the high, medium and low volatility scenarios are $\sigma =$ €4.7/MWh, $\sigma =$ €12.5/MWh and $\sigma =$ €3.3/MWh, respectively.

Figure 7.5: Sample price paths for different volatilities



The graph shows a one week sample path prices with low, medium and high volatility scenario. From the graph it can be observed that the price with high volatility has a higher maximum and lower minimum than the other two prices with medium and low volatility.

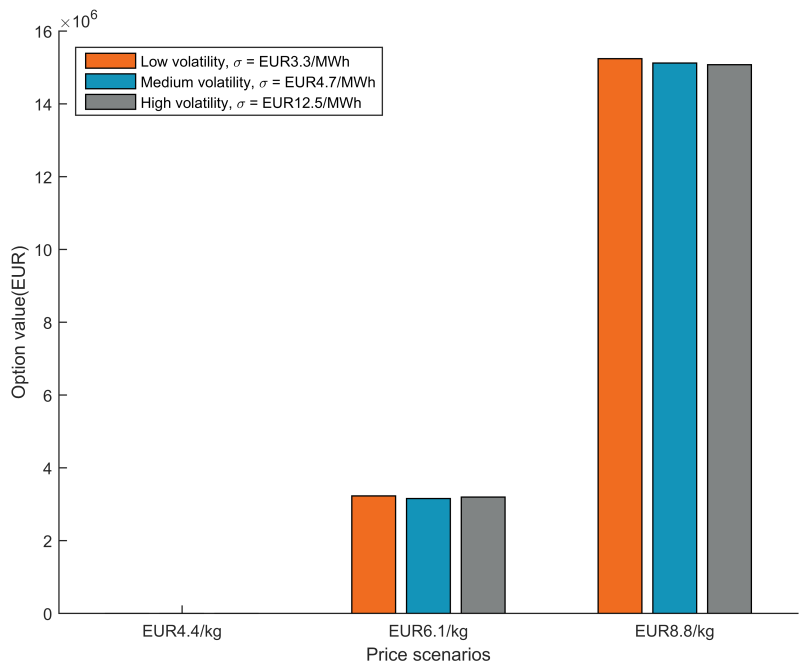
Table 7.2: Model results for low and high electricity price volatility with a hydrogen price of €8.8/kg

	Option value	**Capacity**	**Investment time**	**Usage**	**Utilisation rate**	**H_2 produced per year (tons)**
Low volatility	€15.2M	2	Year 0	100%	62.6%	477
Medium volatility	€15.1M	2	Year 0	99.99%	62.6%	477
High volatility	€15.1M	2	Year 0	99.51%	62.3%	474

Figure 7.6 shows the impact of the price volatility on the option value for the three hydrogen price scenarios. The graph shows that the value of the option is relatively stable across the different volatilities. Table 7.2 further compares the capacity choice, investment timing, usage, utilisation rate and hydrogen produced per year for the different volatilities for P^H =€8.8/kg. Table 7.2 shows that the option values, capacity choice and investment timing is similar across the three volatilities. Moreover, the plant is seldom suspended across the different volatilities and the

hydrogen plant also has similar utilisation rate and production. While not shown here, similar results can be obtained for scenario 2, P^H =€6.7/kg. The reason why the results do not differ significantly across volatility can be explained by the high usage, i.e. the plant is seldom suspended. If the plant is seldom suspended, the mean of the electricity price will be the main determinant of the variable cost. To illustrate why this is the case consider what happens if the volatility is high. The money lost when the price is high is earned when the price is low, given that the hydrogen price is constant. Therefore on average the mean electricity price is paid to produce hydrogen. We therefore conclude that as long as the operation is not suspended the value of flexible operations is low and volatility has little effect on the investment decision.

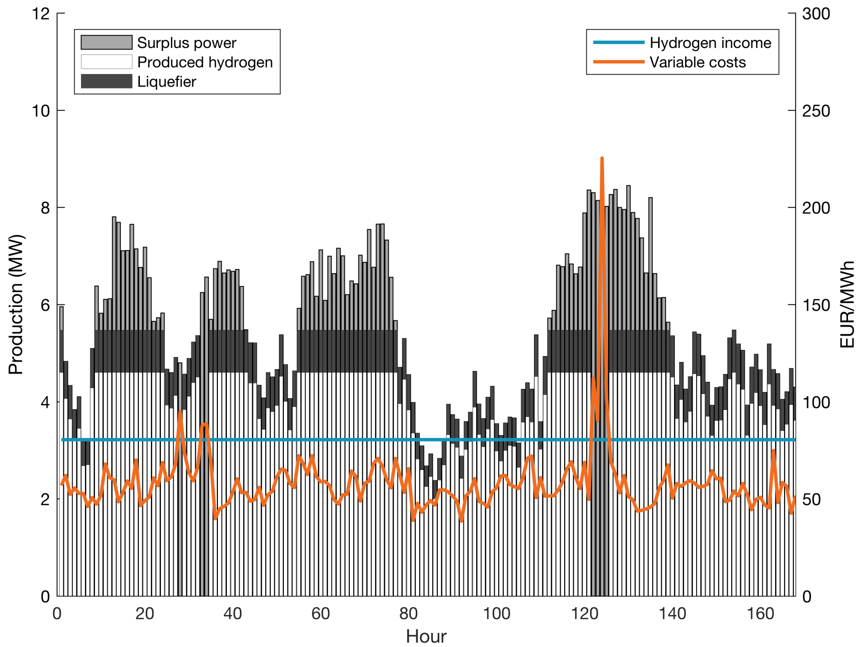
Figure 7.6: Sensitivity of option value with respect to electricity price volatility



The option value is shown for the three different hydrogen price scenarios P^H = €8.8/kg, P^H = €6.1/kg and P^H = €4.4/kg for high, medium and low volatility. The high medium and low volatility is σ = 12.5/MWh, σ = 4.7/MWh and σ = 3.3/MWh, respectively. The graph shows the the option value is not affected significantly by the different volatilities.

To investigate the effect of volatility when the operation of the plant is more often suspended, we set the revenue from selling the hydrogen price closer to the mean of the variable costs. Figures 7.7 and 7.8 illustrate the operation of the plant during an example week with a hydrogen price of €5.05/kg under high and low price volatility.

Figure 7.7: Optimal operation of the hydrogen plant for a hydrogen price of €5.05/kg and high electricity price volatility



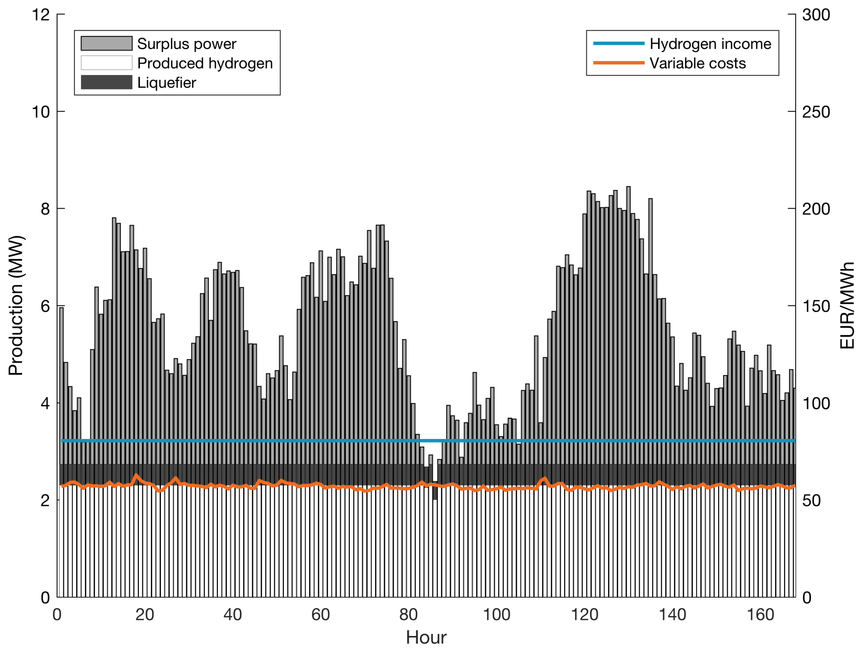
Optimal operation of the plant for an example week is shown for, P^H =€5.05/kg with high electricity price volatility, σ =€12.5/MWh. The operations are suspended several times during the week. The optimal capacity found by the investment model was 2 electrolysers, and the grey part of the bars indicates there is surplus power during the week.

Table 7.3: Model results for low and high electricity price volatility with a hydrogen price of €5.05/kg

	Option value	**Capacity**	**Investment time**	**Usage**	**Utilisation rate**	**H_2 produced per year (tons)**
Low volatility	€640,000	1	Year 10	99.92%	83.76%	319
High volatility	€680,000	2	Year 10	96.27%	60.05%	457

Figure 7.7 shows that the when the variable costs are higher than the hydrogen price, the operations of the hydrogen plant is suspended from time to time. In the low volatility case, shown in Figure 7.8 the operations are never suspended.

Figure 7.8: Optimal operation of the hydrogen plant for a hydrogen price of €5.05/kg and low volatility electricity price volatility, $\sigma =$€3.3/MWh



Optimal operation of the plant for an example week is shown for, P^H =€5.05/kg with low electricity price volatility, $\sigma =$€3.3/MWh. The operations are never suspended during the week. The optimal capacity found by the investment model was 1 electrolyser, and the grey part of the bars indicates there is surplus power during the week.

In Figure 7.7 the prices also drop and have a lower minimum price compared to Figure 7.8. Table 7.3 compares how the two scenarios influences the investment decision. First, Table 7.3 shows that in the high volatility scenario the option value is higher and the investor installs a higher capacity. This results demonstrate the value created by flexibility. By installing a larger capacity he can benefit from the dips in the price and thereby produce larger amounts of hydrogen when the price is low and at the same time avoid losses by suspending operations when the electricity price is high. The table also shows that the total amount produced is higher in the high volatility scenario. However, compared to the low volatility scenario the usage is lower since operations are suspended more often. Moreover, the utilisation rate is also lower since two electrolysers are installed instead of one. In both cases, it is optimal to delay investment in order to benefit from lower investment costs.

Based on these results we draw three main conclusions that an investor should be aware of. First, the hydrogen price would have to decrease significantly from today's level for making it optimal to delay investment. Second, the hydrogen price affects both the investment timing and the optimal capacity to invest in. Third, when the hydrogen price and variable costs approach each other, that the investment decision becomes more sensitive to volatility. In this case the investor benefits from a higher price volatility by investing in a larger capacity and producing when the prices are low and suspend production when prices are high.

Chapter 8

Conclusion

Emission-free hydrogen can be produced from electrolysis using power from renewable energy sources. Hydrogen can be used as an energy carrier across several industries, but is seen to have largest potential as a fuel in the transportation sector. Widespread adoption of hydrogen technologies can therefore support climate change goals in several sectors of the energy system. Most hydrogen technologies are still in the early stages of commercialisation, but the market in several countries is emerging and is expected to grow in the future.

In this thesis, we study a Norwegian power producer considering to become a hydrogen supplier. A real options approach is applied in order to value the opportunity to invest in a hydrogen plant using power from one of its existing wind farms. By investing in a hydrogen plant, the investor can at any point in time choose whether to sell the power produced by the wind farm in the market or use it to produce hydrogen. The optimal decision depends on which alternative yields the highest profit for the investor. The investor need to determine the optimal timing and capacity of the hydrogen plant under flexible operations and uncertainty.

Our model builds on existing literature within real options theory and applies it to the area of wind-hydrogen investments. The model consists of two parts. The first part derives the optimal operation strategy of the hydrogen. The second part derives the optimal timing and capacity for the investment using a LSM approach. While we only consider electricity price uncertainty, the model is very flexible can potentially account for uncertain hydrogen prices and available power from the wind farm.

We investigate the optimal investment strategy through a case study of hydrogen production using wind power from Valsneset in Bjugn municipality in Norway. We assume electricity prices to be uncertain and follow a mean-reverting process with spikes that is calibrated in cooperation with our industry partner. The hydrogen price is assumed deterministic and the model is run for a low, medium and high hydrogen price scenario. The available power is also assumed deterministic and to follow average historical production.

Our results show that it optimal to invest immediately in the high price scenario, delay investment in the medium price scenario and never invest in the low price scenario. The timing of the investment depends on the trade-off between foregoing current profits and waiting for a lower investment cost in the future. With respect to optimal capacity choice, we find that it is optimal to invest in a higher capacity when the hydrogen price increases. This result is similar to Décamps et al. (2006) and Dangl (1999). Moreover, for the three scenarios, the investment decision was not sensitive to the volatility in the electricity price because operations were rarely suspended. In contrast, the investment decision was shown to be sensitive to electricity when the hydrogen price was close to variable costs and the volatility was high. In fact, the option value and optimal capacity to invest in was increased with a higher volatility. By investing in a higher capacity, the flexible operations allow the firm to produce larger amounts of hydrogen when the price is low and suspend operations when the price is high. We therefore get a similar result as Floch et al. (2007): When the volatility is high and operations are suspended the value of flexibility is higher.

Based on the results we draw three main conclusions. First, the hydrogen price would have to decrease significantly from today's level to make it optimal to delay investment. Second, the hydrogen price affects both the investment timing and the optimal capacity to invest in. Third, if the hydrogen price and variable costs approach each other, the investment decision becomes more sensitive to volatility. In this case, the investor benefits from higher volatility by installing a larger capacity. By installing a larger capacity he can produce greater amounts of hydrogen when electricity prices are low and avoid loss by suspending operations when prices are high.

Our main contribution has been twofold. First, we have contributed to the real options literature by studying the combined problem of determining optimal timing and capacity choice as well as optimising plant operations under uncertainty. To solve the problem we have used LSM and demonstrated its practical applicability. Second, we have applied a real options valuation to a specific hydrogen investment case that has the potential to capture the upside potential of uncertainty. For different scenarios of the price of hydrogen we have found different investment strategies and thereby add to the ongoing discussion of the economic viability of hydrogen production from wind power.

However, regardless of the compelling results, the model is based on several assumptions that limit the applicability of the absolute values presented. We therefore emphasise that our models mainly contributes towards giving intuition on how uncertainty in electricity price affects investment problem.

Extensions of our research is possible in several directions:

- **Modeling flexible operations of the hydrogen plant:** In the thesis we have made several simplifications regarding the operation of the hydrogen plant. First, we have assumed that that the efficiency of the electrolyser is constant across all power loads and that voltage degradation does not occur. This is not the case in reality. Formulating an optimisation model with varying efficiency across loads is possible. By accounting for varying electricity, the authors developed a nonlinear optimisation model. This would require further manipulations in order to be solved with a reasonable running time, because a nonlinear program is more complex to solve than a linear program (Hochbaum, 2007). Second, we assume that the electrolyser can operate between a load of 0% and 100%. However, in reality it has an operating range between 20% and 100%. We ignore this restriction because it had to be modelled using a Mixed-Integer Linear Programming which was very time consuming to solve over the whole lifetime of the plant. Further research is required in order to find more efficient solutions to this problem. Third, we assume that there is no start-up and shutdown time for the electrolyser. In reality, this can take several minutes. However modeling this also required a Mixed-Integer Linear Programming approach for which we need solutions that are more efficient.

- **Modeling risk factors:** The only risk factor modelled in this thesis is the electricity price. We developed an electricity price model in collaboration with our industry partner and assumed that the price followed a mean-reverting process with jumps. However, a disadvantage with the model is that it does not capture the clustering effect of spikes. This could have been captured by using a Markov regime-switching model similar to Bakke et al. (2016). However, we also propose that the Markov regime-switching model should take into account the long-term equilibrium level given by a Schwartz-Smith model which has been described in this thesis. Moreover, treating both the hydrogen price and the available power as uncertain is another possible extension. When more information is available, the hydrogen price can be assumed to follow any stochastic uncertain process. Regarding the available power, using the models for output uncertainty proposed by Adkins & Paxson (2016), Munoz et al. (2009) or Abadie & Chamorro (2014) could be a possible extension. However, other possible uncertainties could also be interesting to model. As we have touched upon there is significant technological uncertainty regarding technological developments. Therefore modeling technological uncertainty along the lines of Murto (2007) where a technological development is modelled by assuming that the investment cost follows a geometric Brownian motion (GBM) with Poisson jumps.

- **Use framework conditions:** We model a wind-hydrogen production where we assume that the power available is the power the wind farm produces. Thus, we assume that the electrolyser can not draw power from the grid. Only using power from the wind farm restricts the amount of hydrogen produced. A possible extension is to model a grid-connected wind farm. This model would not be restricted by available power, and therefore developing a more stylistic model along the lines of costless suspension and resumption in Dixit & Pindyck (1994) could be possible. This model could have been extended to include capacity choice.

- **Incremental capacity:** In this thesis, we have assumed that the capacity is fixed once the investment is undertaken. However, the investment in the hydrogen plant is modular. Incorporating the flexibility to increase capacity along the lines of Pindyck (1988) could also be a possible extension.

- **Reducing computing time:** Since we find the optimal operation of the hydrogen over the whole lifetime of the project the running time of our model is very high. More efficient methods in order to find the optimal operation of the plant and the maximised project would require further research.

- **Time from investment decision to the project starts to operate:** From the time an investor decide to invest the hydrogen plant until it is operating can approximately one year. This time is not included in our model. This lagging period caused by construction reduces the value of the investment because it does not generate any profits and could affect the timing of the investment. To extend our valuation it would be favourable to include a lagging period along the lines of Linnerud et al. (2014) which includes the construction lag as a parameter in the electricity price

- **Compare investment strategy for inflexible production:** Another possible extensions could be to model flexible and inflexible production along the lines of Hagspiel et al. (2016). Since different electrolysers offer different levels of flexibility, this could offer a way of comparing the value of different electrolysers to each other.

Appendix A

Least Square Monte Carlo

LSM is a recursive algorithm that at each step, y, compares the payoff from exercise with the continuation value. At each time step, LSM approximates the continuation function $W_y = \frac{1}{1+\rho}\mathbb{E}[F_{y+1}|V(Q)_y]$ using basis functions in set $\Phi_i = \{\phi_{y,b}, b = 1, ..., B_y\}$ where B_y is the number of basis functions at stage y. Each $\phi_{y,b}$ is a function of $V(Q)_y$.

The continuation function approximation at $V(Q)_y$ is defined as:

$$\Phi_y, \beta_y = \sum_{b=1}^{B} \phi_{y,b}(V(Q)_y)\beta_{y,b} \tag{A.0.1}$$

where $\beta_{y,b}$ is the coefficient in front of basis function b at time stage y and exogenous state $V(Q)_y$.

The steps of the LSM procedure are as follows. First we use the Monte Carlo simulations of the exogenous information. We let $V(Q)_{iy}$ represent the stage y exogenous factor on sample path i. The terminal values F_{iM} are calculated as:

$$F_{iM} = \max(0, V(Q)_{iM}) \tag{A.0.2}$$

Then moving backwards from stage $M-1$ to stage 0, at each stage $y \in M-1, ..., 0$ we (1) compute the value estimates along each sample path i using the stage $y+1$ continuation function approximation:

$$w_y = \frac{1}{1+\rho}(\Phi_{y+1}, \beta_{y+1})(V(Q)_{y+1}) \tag{A.0.3}$$

and (2) compute the coefficients $\beta_{y,b}, \forall b$ by performing least squares regression on the estimates $w_y, \forall i$. Values of the state variables at the current time step are used as explanatory variables in the regression, and the continuation values of the different operating states are regressed on these.

Possible choices for a regression basis mentioned by Longstaff & Schwartz (2001) are Laguerre, Hermite and Jacobi polynomials as well as only simple powers of the state variables. In the model used in this thesis, we choose to use the first three degrees of simple polynomials:

$$\Phi_{y,0}(V(Q)_y) = 1 \tag{A.0.4}$$

$$\Phi_{y,1}(V(Q)_y) = V(Q)_y \tag{A.0.5}$$

$$\Phi_{y,2}(V(Q)_y) = V(Q)_y^2 \tag{A.0.6}$$

The approximate continuation values therefore follow the distribution:

$$(\Phi_y, \beta_i)(V(Q)_y) = \beta_0 + \beta_1 V(Q)_y + \beta_2 V(Q)_y^2. \tag{A.0.7}$$

where β_0, β_1 and β_2 are the constants that are being estimated at each time step. Having a functional form of conditional expectation function, we can now compare the value of immediate exercise versus continuation at each date y along the path i.

The value of the option is determined by summing all the payoff paths at time zero and average the payoff over the number of paths, B:

$$\text{Option value} = \frac{1}{N}\sum_{i=1}^{N} V(Q)_{i0} \tag{A.0.8}$$

Appendix B

Matlab and Mosel code

The digital appendix contains the necessary code to run the model. The following files are added:

- **AR1_ElPriceModel.m** - The long-term price process is modeled from the EMPS in this script.
- **CashFlowXpress.m** - Interacts with Xpress and retrieves the cash flows from Xpress.
- **InvestmentCost.m** - Function that outputs the investment cost given year invested and capacity Q chosen.
- **LeastSquareMonteCarlo.m** - The Least-Square Monte Carlo process that outputs the year of exercise and option value.
- **Main.m** - The script that couples the other functions together.
- **MoselModel.mos** - The optimisation model run in Xpress.
- **OrnsteinUhlenbeck.m** - The short-term price process is modeled in this function. Outputs 1 week of prices.
- **WeekToHour** - Couples the long-term prices with the short-term prices.

References

Aas, E. F., & Andresen, S. H. (2015). *Operation, Valuation and Electricity Sourcing for a Generic Aluminium Smelter*. Master's thesis Norwegian University of Science and Technology NO 7479 Trondheim, Norway.

Abadie, L. M., & Chamorro, J. M. (2014). Valuation of wind energy projects: a real options approach. *Energies*, *7*, 3218–3255.

Adkins, R., & Paxson, D. (2016). Subsidies for renewable energy facilities under uncertainty. *The Manchester School*, *84*, 222 – 250.

Agency for Natural Resources and Energy (2014). *Summary of the Strategic Road Map for Hydrogen and Fuel Cells*. Agency for Natural Resources and Energy. Available at `http://www.meti.go.jp/english/press/2014/pdf/0624_04a.pdf`.

Alesii, G. (Forthcoming). Assessing least squares monte carlo for the kulatilaka trigeorgis general real options pricing model. Working paper.

Alexander, C. (2008). *Market Risk Analysis, Volume I, Quantitative Methods in Finance*. West Sussex: John Wiley & Sons, Ltd.

Aronsen, G. (2016). Personal communication.

Bakke, I., Fleten, S.-E., Hagfors, L. I., Hagspiel, V., Norheim, B., & Wogrin, S. (2016). Investment in electric energy storage under uncertainty: a real options approach. *Computational Management Science*, . 1-18.

Bernal-Agustín, J. L., & Dufo-López, R. (2008). Hourly energy management for grid-connected wind–hydrogen systems. *International Journal of Hydrogen Energy*, *33*, 6401–6413.

Bertuccioli, L., Chan, A., Hart, D., Lehner, F., Madden, B., & Eleanor (2014). *Development of Water Electrolysis in the European Union*. E4tech Sàrl with Element Energy Ltd for the Fuel Cells and Hydrogen Joint Undertaking. Available at `http://www.fch.europa.eu/sites/default/files/study20electrolyser_0-Logos_0.pdf`.

Boomsma, T. K., Meade, N., & Fleten, S.-E. (2012). Renewable energy investments under different support schemes: A real options approach. *European Journal of Operational Research*, *220*, 225 – 237.

Bøckman, T., Fleten, S.-E., Juliussen, E., Langhammer, H. J., & Revdal, I. (2008). Investment timing and optimal capacity choice for small hydropower projects. *Energy Policy*, *190*, 255–267.

Chronopoulos, M., Reyck, B. D., & Siddiqui, A. (2011). Optimal investment under operational flexibility, risk aversion, and uncertainty. *European Journal of Operational Research*, *213*, 221 – 237.

Chronopoulos, M., Reyck, B. D., & Siddiqui, A. (2013). The value of capacity sizing under risk aversion and operational flexibility. *IEEE Transactions on Engineering Management*, *60*, 272 – 288.

Cortazar, G., Gravet, M., & Urzua, J. (2008). The valuation of multidimensional american real options using the lsm simulation method. *Computers & Operations Research*, *35*, 113 – 129. Part Special Issue: Applications of OR in Finance.

Dahl, P. I., Bünger, U., Völler, S., Korpås, M., & Møller-Holst, S. (2013). *Hydrogen for transport from renewable energy in Mid-Norway*. SINTEF. Available at `http://www.transnova.no/wp-content/uploads/2012/07/H2iMidtNorge_Sluttrapport.pdf`.

Dangl, T. (1999). Investment and capacity choice under uncertain demand. *European Journal of Operational Research*, *117*, 415–428.

Décamps, J.-P., Mariotti, T., & Villeneuve, S. (2006). Irreversible investment in alternative projects. *Economic Theory*, *28*, 425–448.

Dias, M. A. G., Rocha, K., & Teixeira, J. P. (Eds.) (2004). *The optimal investment scale and timing: A real option approach to oilfield development*.

Dillich, S., Ramsden, T., & Melaina, M. (2012). *Hydrogen Production Cost Using Low-Cost Natural Gas*. U.S. Department of Energy. Available at `https://www.hydrogen.energy.gov/pdfs/12024_h2_production_cost_natural_gas.pdf`.

Dixit, A. K., & Pindyck, R. S. (1994). *Investment under uncertainty*. New Jersey: Princeton university press.

DNV-GL (2015). Hydrogen and Japan. Report No. 2015-0799, Rev. 1, Available at `https://www.dnvgl.com/news/a-new-era-for-hydrogen-energy-unveiled-by-summer-students-at-dnv-gl-33379`.

Dutton, A., Bleijs, J., Dienhart, H., Falchetta, M., Hug, W., Prischich, D., & Ruddell, A. (2000). Experience in the design, sizing, economics, and implementation of autonomous wind-powered hydrogen production systems. *International Journal of Hydrogen Energy*, *25*, 705 – 722.

Fleten, S.-E., Maribu, K., & Wangensteen, I. (2007). Optimal investment strategies in decentralized renewable power generation under uncertainty. *Energy*, *32*, 803 – 815.

Fleten, S.-E., & Näsäkkälä, E. (2010). Gas-fired power plants: Investment timing, operating flexibility and co_2 capture. *Energy Economics*, *32*, 805 – 816. Policy-making Benefits and Limitations from Using Financial Methods and Modelling in Electricity Markets.

Fleten, S.-E., Wallace, S. W., & Ziemba, W. T. (2002). Hedging electricity portfolios via stochastic programming. In *Decision Making Under Uncertainty* (pp. 71–93). Springer.

Floch, P.-H., Gabriel, S., Mansilla, C., & Werkoff, F. (2007). On the production of hydrogen via alkaline electrolysis during off-peak periods. *International Journal of Hydrogen Energy*, *32*, 4641–4647.

Fraile, D., Lanoix, J.-C., Maio, P., Rangel, A., & Torres, A. (2015a). *Bibliographic review of market outlooks for hydrogen in Europe*. CertifHy. Available at `http://www.fch.europa.eu/sites/default/files/project_results_and_deliverables/D201.1.20Bibliographic20review20of20market20outlooks20for20hydrogen20in20Europe.pdf`.

Fraile, D., Lanoix, J.-C., Maio, P., Rangel, A., & Torres, A. (2015b). *Generic estimation scenarios of market penetration and demand forecast for "pre-*

mium" green hydrogen in short, mid and long term. CertifHy. Available at http://www.certifhy.eu/images/D1_3_Hydrogen_Market_Outlook_24_June_2015__low-res.pdf.

Fraile, D., Lanoix, J.-C., Maio, P., Rangel, A., & Torres, A. (2015c). *Overview of the market segmentation for hydrogen across potential customer groups, based on key application areas*. CertifHy. Available at http://www.certifhy.eu/images/D1_2_Overview_of_the_market_segmentation_Final_22_June_low-res.pdf.

Freedonia (2012). *World Hydrogen: Industry Study with Forecasts for 2016 & 2021*. The Freedonia Group. Available at http://www.freedoniagroup.com/brochure/28xx/2895smwe.pdf.

González, A., McKeogh, E., & Gallachóir, B. (2004). The role of hydrogen in high wind energy penetration electricity systems: The irish case. *Renewable Energy*, *29*, 471–489.

Greiner, C. J., Korpås, M., & Holen, A. T. (2007). A norwegian case study on the production of hydrogen from wind power. *International Journal of Hydrogen Energy*, *32*, 1500 – 1507.

Gutiérrez-Martín, F., Confente, D., & Guerra, I. (2010). Management of variable electricity loads in wind – hydrogen systems: The case of a Spanish wind farm. *International Journal of Hydrogen Energy*, *35*, 7329–7336.

Gutiérrez-Martín, F., María, J. M. G.-D., Baïri, A., & Laraqi, N. (2009). Management strategies for surplus electricity loads using electrolytic hydrogen. *International Journal of Hydrogen Energy*, *34*, 8468–8475.

Hagspiel, V., Huisman, K. J., & Kort, P. M. (2016). Volume flexibility and capacity investment under demand uncertainty. *International Journal of Production Economics*, *178*, 95 – 108.

Hamanaka, I. (2015). Hydrogen and Japan. PowerPoint Presentation, Available at http://www.hydrogen.no/maritim-bergen-sept2014/Hydrogen20related20activities 20in 20Japan 20DNV 20GL 20Ikuo 20Hamanaka.pdf.

Hochbaum, D. S. (2007). Complexity and algorithms for nonlinear optimization problems. *Annals of Operations Research*, *153*, 257–296.

Huberts, N. F. D., Huisman, K. J. M., Kort, P. M., & Lavrutich, M. N. (2015).

Capacity choice in (strategic) real options models: A survey. *Dynamic Games and Applications*, *5*, 424–439.

HyWays (2008). *HyWays the European Hydrogen Roadmap*. European Comission. Available at `http://cordis.europa.eu/pub/fp7/energy/docs/hyways-roadmap_en.pdf`.

IEA (2015). *Technology Roadmap Hydrogen and Fuel Cells*. International Energy Agency. Available at `https://www.iea.org/publications/freepublications/publication/TechnologyRoadmapHydrogenandFuelCells.pdf`.

Jørgensen, C., & Ropenus, S. (2008). Production price of hydrogen from grid connected electrolysis in a power market with high wind penetration. *International Journal of Hydrogen Energy*, *33*, 5335–5344.

Korpås, M. (2004). *Distributed Energy Systems with Wind Power and Energy Storage*. Ph.D. thesis Norwegian University of Science and Technology.

Kvaal, B. (2016). Personal communication.

Körner, A. (2015). *Technology Roadmap Hydrogen and Fuel Cells Technical Annex*. International Energy Agency. Available at `https://www.iea.org/media/freepublications/technologyroadmaps/TechnologyRoadmapHydrogen_Annex.pdf`.

Linnerud, K., Andersson, A. M., & Fleten, S.-E. (2014). Investment timing under uncertain renewable energy policy: An empirical study of small hydropower projects. *Energy*, *78*, 154 – 164.

Longstaff, F. A., & Schwartz, E. S. (2001). Valuing american options by simulation: A simple least-squares approach. *Rev. Financ. Stud.*, *14*, 113–147.

Løland, L. (2015). *Analysis of Grid-Connected Wind Farm Combined With Hydrogen Production*. Master's thesis Norwegian University of Life Sciences Universitetstunet 3, 1430 Ås.

Maisonnier, G., Perrin, J., Steinberger-Wilckens, R., & Trümper, S. C. (2007). *PART II: Industrial surplus hydrogen and markets and production*. Roads2Hy. Available at `http://www.ika.rwth-aachen.de/r2h/images/d/df/Roads2HyCom_R2H2006PU_-_(Part_II)_-_Industrial_Surplus_H2.pdf`.

McDonald, R., & Siegel, D. (1986). The value of waiting to invest. *Quarterly Journal of Economics*, *101*, 707 – 727.

McKinsey & Company (2010). *A portfolio of power-trains for Europe: a fact-based analysis*. McKinsey & Company. Available at https://europeanclimate.org/documents/Power_trains_for_Europe.pdf.

Munoz, J., Contreras, J., Caamano, J., & Correia, P. (2009). Risk assessment of wind power generation project investments based on real options. In *PowerTech, 2009 IEEE Bucharest* (pp. 1–8). IEEE.

Murto, P. (2007). Timing of investment under technological and revenue-related uncertainties. *Journal of Economic Dynamics & Control*, *31*, 1473–1497.

Muyeen, S., Takahashi, R., & Tamura, J. (2011). Electrolyzer switching strategy for hydrogen generation from variable speed wind generator. *Electric Power Systems Researchy*, *81*, 1171–1179.

Myhre, A. (2016). Available at http://www.hegnar.no/TV/video/0647c164-00080348-e4e35352 Video clip HegnarTV.

Møller-Holst, S. (2016). Personal communication.

Møller-Holst, S., & Thomassen, M. (2015). *Analyse av alternative driftsformer for ikke-elektrifiserte baner*. SINTEF. Available at https://europeanclimate.org/documents/Power_trains_for_Europe.pdf.

Nadarajah, S., Margot, F., & Secomandi, N. (2015). Relaxations of approximate linear programs for the real option management of commodity storage. *Management Science*, *61*, 3054 – 3076.

NEL Hydrogen (2015). *Efficient electrolysers for hydrogen production*. NEL Hydrogen. Available at http://wpstatic.idium.no/www.nel-hydrogen.com/2015/03/Efficient_Electrolysers_for_Hydrogen_Production.pdf.

Nord Pool (2016). The power market. Available at http://www.nordpoolspot.com.

Pedrazzi, S., Zini, G., & Tartarini, P. (2012). Modelling and simulation of a wind-hydrogen CHP system with metal hydride storage. *Renewable Energy*, *46*, 14 – 22.

Pindyck, R. S. (1988). Irreversible Investment, Capacity Choice, and the Value of the Firm. *American Economic Review*, *78*, 969–85.

Roadmap 2050 (2010a). *A practcal guide to a prosperous, low-carbon Europe*. Roadmap 2050. PowerPoint presentation, Available at `http://www.roadmap2050.eu/attachments/files/Corepresentation.pdf`.

Roadmap 2050 (2010b). *A practical guide to a prosperous, low-carbon Europe*. Roadmap 2050. Available at `http://www.roadmap2050.eu/attachments/files/Volume1_fullreport_PressPack.pdf`.

Schwartz, E., & Smith, J. E. (2000). Short-term variations and long-term dynamics in commodity prices. *Management Science*, *46*, 893–911.

Schwartz, E. S. (1997). The stochastic behavior of commodity prices: Implications for valuation and hedging. *The Journal of Finance*, *5*, 923 – 973.

Sen, S., Yu, L., & Genc, T. (2006). A stochastic programming approach to power portfolio optimization. *Operations Research*, *54*, 55 – 72.

SINTEF (2016). Emps Multi area power market simulator. Available at `https://www.sintef.no/en/software/emps-multi-area-power-market-simulator/`.

Smelvær, I. S. (2015). *Analysis of the Norwegian-Swedish Market for Green Certificates Using the EMPS Model*. Master's thesis Norwegian University of Science and Technology.

Stolzenburg, K., & Mubbala, R. (2013). *Fuel Cells and Hydrogen Joint Undertaking*. IDEALHY.

The Norwegian Hydrogen Council (2012). *Action Plan 2012-2015*. The Norwegian Hydrogen Council. Available at `http://www.hydrogen.no/assets/files/Hydrogenradet/Handlingsplan/The_Norwegian_Hydrogen_Council_Action-plan_2012-2015.pdf`.

Thompson, M. (2013). Optimal economic dispatch and risk management of thermal power plants in deregulated markets. *Operations Research*, *61*, 791 – 809.

Thompson, M., Davison, M., & Rasmussen, H. (2009). Natural gas storage valuation and optimization: A real options application. *Naval Research Logistics*, *56*, 226 – 238.

Tomasgard, A., Møller-Holst, S., Thomassen, M., Bull-Berg, H., Damman, S., & Bjørkvoll, T. (2016). *Nasjonale rammebetingelser og potensial for hydrogensatsingen i Norge*. SINTEF. Available at `http://www`

.jernbaneverket.no/contentassets/24510efa7bb04f799e9b57961b3e4b9d/alternative-driftsformer-kunnskapsgrunnlag-sintef.pdf.

Tzimas, E., Peteves, C. F. S., & Veyret, J.-B. (2003). *Hydrogen storage: State-of-the-art and future perspective*. European Commission Directorate General Joint Research Centre (DG JRC). Available at http://publications.jrc.ec.europa.eu/repository/bitstream/JRC26493/EUR202099520EN.pdf.

United States Department of Energy (2002). *National Hydrogen Energy Roadmap*. United States Department of Energy. Available at https://www.hydrogen.energy.gov/pdfs/national_h2_roadmap.pdf.

Valdés, R., Lucio, J., & Rodríguez, L. (2013). Operational simulation of wind power plants for electrolytic hydrogen production connected to a distributed electricity generation grid. *Renewable Energy*, *53*, 249 – 257.

Weron, R. (2014). Electricity price forecasting: A review of the state-of-the-art with a look into the future. *International Journal of Forecasting*, *30*, 1030 – 1081.

Yang, C., & Ogden, J. (2007). Determining the lowest-cost hydrogen delivery mode. *International Journal of Hydrogen Energy*, *32*, 268 – 286.

Zeng, K., & Zhang, D. (2010). Recent progress in alkaline water electrolysis for hydrogen production and applications. *Progress in Energy and Combustion Science*, *36*, 307–326.