Competing Technologies in Transport

Battery, hydrogen, or both?

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Abstract

The transport sector is one of the most important sectors when it comes to mitigating climate change, as it accounts for almost a quarter of all energy-related CO_2 emissions. The development of emission-free transport technologies, like batteries, have gained increased attention in later years. However, hydrogen technology has also a large potential regarding emission-free transport, but is today costlier than the battery approach. This thesis analyzes whether it is optimal to use one or both of these technologies, when todays preferred fossil technology is present. This is done by constructing a dynamic model, where learning in the two clean technologies is endogenized, so that future costs in these technologies could be reduced. The analysis shows that it could be optimal to support the clean technologies. The model is then simulated using realistic estimates for the initial costs of the different technologies. The simulations states that it could be optimal to use both battery and hydrogen throughout the next century, while fossil fuel is phased out in the same period. This result is however dependent upon the parameter values used, and it is shown that the results are sensitive to changes in these.

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All remaining mistakes are my responsibility.

Contents

List of Tables

List of Figures

1 Introduction

As more and more research on climate change have been conducted over the last decades, there is a growing consensus, both among scientists and in the public, that the problem we are facing is largely due to greenhouse gas (GHG) emissions stemming from human activity. This certainty is expressed by the International Panel on Climate Change (IPCC) in that they are "now 95% certain that humans are the main cause of current global warming" (IPCC, 2014, p. v). In other words, the debate does not longer revolve around whether the changes we are facing are man made, but how to best deal with the issue.

In 2011 the European Commission published a roadmap for moving towards a low-carbon and competitive economy in 2050. The goal is to reduce GHG emissions in the EU by 80% by 2050 compared to 1990. In that respect, the transport sector plays a crucial role, as it accounts for 23% of all energy-related CO_2 emissions both in the EU and the world as a whole (IEA, 2017; European Commission, 2017). Of the transport emissions in the EU, road transport is the solely largest emitter, and accounts for more than 70% of all GHG emissions in this sector in 2014 (European Commission, 2017). Transport is also the only major emission sector in the EU where emissions still rises. In other words, the transport sector is a major concern for EU governments. The goal for the transport sector in the EU is to reduce total emissions by 60% in 2050 relative to 1990 levels.

As a measure to reduce emissions from transport, battery electric vehicles (BEVs) have gained increased support over the last few years. This is partially due to the fact that the previous high cost has been significantly reduced through improved technology. Particularly the battery costs have seen a declining trend in later years, which have made many optimistic about the future possibilities that lies in BEVs. Still, these vehicles face several challenges for being competitive with the conventional internal combustion engine (ICE) vehicle: it faces a trade-off between energy capacity and weight; have challenges when it comes to recharging time and range; and it still has a higher cost. In addition to BEVs, there are other types of electric vehicles, also considered to be a *clean* alternative compared to the fossil technology used in an ICE.

In contrast to storing energy in a battery, fuel cell electric vehicles (FCEV) use hydrogen for running an electric drivetrain. FCEVs shares many of the same features as the conventional fossil fuel based vehicle. The range is relatively similar, the refueling takes place at stations, and the refueling will be over in a few minutes, which is in contrast to the BEVs. And even though BEVs have gained an advantage when it comes to mass production relative to the FCEVs, some see the latter type as a better alternative for combating the GHG emissions from the transport sector in the longer run, often with an argument that FCEVs have a higher potential for cost reductions, than the BEVs. This view will be elaborated below.

The object in this thesis, is to shed light on the relationship between fossil technology, battery technology and hydrogen technology for road transport, including commercial and private transport. More specifically, whether the hydrogen technology is optimal to introduce at a high scale, either *together* with BEVs, or by itself. It is also important to see how these technologies affect the use of fossil technology, which runs the vast majority of all road transport in EU today. Will the fossil technology cease to be used, and if so, at which rate? Also, it will be examined whether there should be some sort of public support directed toward the clean technologies, or if it is reason to believe that this is not necessary, given that emission from fossil fuels are taxed. This could be the case if either it is not optimal to utilize the technology at all, or if the future costs will decline at a sufficient rate 'on its own', which will make it attractive by a market solution without any support.

A well established approach for endogenizing technological change, which in turn leads to cost reductions, is to use *learning curves*. These describe the negative relationship between accumulated production, and the costs related to this production. In other words, as the production increases, the costs tend to decline, explained by the increased learning and gained experience. The research questions stated above will be addressed using a theoretical model which includes learning.

The remainder of the thesis is structured as follows: Section 2 introduces the technologies for hydrogen and battery used for transportation. Section 3 provides a literature review of the analytical framework that will be used in Section 4, where the theoretical model is introduced. In Section 5, the model will be adjusted for making simulations using the Excel Solver add-in[1], which in turn could give some indications of future development of the technologies in focus. Section 6 will discuss the method used and scenarios put forward, before Section 7 provides some possible extensions to the model together with further research questions. Finally, Section 8 will conclude the findings of the thesis.

[1]The spreadsheets are available upon request.

2 Introduction of the technologies

The following section introduce the two technologies that will be subject to learning in the theoretical model. This is done to show what potential there is for cost reductions in these technologies, and also so that one is aware of the main barriers to commercialization that exist today. Further, as both FCEVs and BEVs uses an electric powertrain, the main difference with respect to cost reductions between these vehicles, will be in the fuel cells and batteries respectively (Le Duigou and Smatti, 2014). In other words, this thesis will focus on hydrogen technology used in FCEVs, and battery technology for the BEVs[2], in addition to the production of hydrogen itself, using so called electrolyzers.

2.1 Hydrogen technology

Hydrogen has the highest energy-to-mass ratio of any chemical, is non-toxic and carbon-free (Schlapbach, 2009). As a transport fuel, it has the advantage that it could cut all greenhouse gas emissions in this sector.

Unlike coal, oil and natural gas, but similar to electricity, hydrogen is an energy *carrier*, and not a direct source of energy itself (Greaker and Heggedal, 2010). Therefore, hydrogen needs to be produced. Water is the most abundant source of hydrogen, but to split water (H_2O), you need energy. Following the first law of thermodynamics, the energy required is higher than the energy that can be released from the production (Barbir, 2005), due to the loss of energy. The energy needed could come from renewable energy sources like sunlight or windmills, so from a sustainability point of view, the interaction between hydrogen, electricity and renewable energy sources is thus particularly interesting (Barbir, 2005). Still, the production of hydrogen could also be from fossil fuels like natural gas and coal, and is today the by far most used approach for producing hydrogen (Hosseini and Wahid, 2016). In other words, even though hydrogen in itself does not contain any carbon, it could nevertheless have a significant carbon footprint (Körner et al., 2015).

The main attraction to a hydrogen car, or fuel cell electric vehicle, is that the range could be 500km or more in just one tank, before being refilled in just a couple of minutes. I.e. in much the same fashion as a conventional car (The Economist, 2017). And as

[2]This implies that there will be no explicit analyzes towards other types of electric vehicles, like hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEV).

many believes that drivers will demand similar convenience as for conventional cars today, vehicles using fuel cells is proposed as an attractive solution (ibid.).

For the hydrogen technology used for transport, there are mainly two distinct processes where the potential for cost reductions are highest, namely the electrolyzer technology and the fuel cells. The former refers to the production of the hydrogen itself, while the latter is based on the utilization of the hydrogen in the vehicles.

2.1.1 Electrolyzer technology

Water electrolysis has benefits compared to other ways of producing hydrogen, due to the lack of carbon footprint if it is integrated with a renewable energy source (Ayers et al., 2010). It is a chemical reaction created by electricity which makes it possible to separate elements from each other when they are originally chemically bounded to other substances. This reaction takes place in an electrolyzer. There are mainly two types of low temperature electrolysis that is commercially available, Proton exchange membrane (PEM) electrolysis, and alkaline electrolysis (Ayers et al., 2010). The alkaline electrolysis use a liquid electrolyte[3], whereas the PEM electrolysis use a solid polymer electrolyte (Ayers et al., 2010). Especially the Proton Exchange Membrane (PEM) type, have a high potential for producing hydrogen from renewable energy sources in a decentralized production process (Millet et al., 2010), and thus provide a sustainable solution to produce hydrogen (Carmo et al., 2013). Partly due to the fact that the PEM electrolysis has a significant safety advantage (Ayers et al., 2010), it is a preferred choice for the transport sector. It can also operate at a higher current density, which in turn reduces the operational costs and thus potentially the overall cost of the electrolysis (Carmo et al., 2013).

2.1.2 Fuel cells

A fuel cell is an energy converter that transforms the chemical potential energy that in hydrogen, to heat and electricity, with water as a residual product (Scandinavian Hydrogen Highway Partnership). A fuel cell works like electrolysis, like for the electrolyzer technology, but in reverse (The Economist, 2017). Where electrolysis splits water into hydrogen and oxygen using electricity, a fuel cell combines those two gases to produce

[3] The substance that carries the electrically charged particles from the one electrode to the other.

water and electricity (ibid.). Fuel cells can be used to produce electricity for an electric engine, and the efficiency[4] is relatively high in both the fuel cell and in the electric engine. For example, the FCEV will be about twice as efficient compared to a regular ICE car (Scandinavian Hydrogen Highway Partnership). Fuel cells are also well-suited for use in large electric vehicles such as trains, buses and trucks (Campillo et al., 2017).

There are mainly six different types of fuel cells (Gallucci and van Sint Annaland, 2015). However, they all share some basic features. Every fuel cell has two electrodes, an anode and a cathode. In addition, the fuel cell uses an electrolyte. Also included in the fuel cell, is a catalyst, i.e. a substance that increases the rate of the chemical reaction by lowering the reaction energy for the other substances (Ung Energi, 2016). Compressed hydrogen from a tank is delivered to the anode side, while air from the surroundings is pumped to the cathode side (The Economist, 2017).

The catalyst in the fuel cell makes the hydrogen undergo an oxidation process so that the hydrogen molecule is split into protons and electrons, where the latter is forced to take a detour from the anode to the cathode, while the protons passes through a special membrane. On this detour, the electrons deliver current to an electric motor before reaching the cathode (The Economist, 2017). Here, the electrons get back to the protons before the hydrogen molecule reacts with oxygen, which results in water.

Of the different fuel cells, the proton exchange membrane fuel cell (PEMFC[5]) are the most commercially produced type of fuel cells when it comes to the transportation sector (Holton and Stevenson, 2013), which makes it the most relevant fuel cell for this thesis. One advantage is that it can be started from an ambient temperature, i.e. the temperature of the surrounding air, and also that it runs at a relative low temperature, around 80°C (Campillo et al., 2017).

Except from the fuel cell, a FCEV works in much of the similar fashion as a battery electric vehicle (BEV). The electricity that is generated in the PEMFC runs an electric engine. Instead of storing electricity in internal batteries like in the BEVs (elaborated below), FCEV stores hydrogen in high pressure tanks, and converts this into electricity with the use of a fuel cell stack (Campillo et al., 2017). When using the fuel cell, there is also need for an internal battery, but much smaller, and hence lighter, than in the

[4]The share of the energy released relative to the energy input.

[5]Proton Exchange Membrane are sometimes referred to as Polymer Electrolyte Membrane, which conveniently results in the same acronym.

standard BEVs. It also has the possibility to charge the battery in times when there is a surplus in the electricity production (Ung Energi, 2016). The technology also makes it possible to increase the driving range compared to BEVs to lengths fully comparable to regular ICEs. In addition, the time to fill up the tank is much shorter than what it takes to charge the EV's (Office of Energy Efficiency & Renewable Energy).

2.1.3 Barriers to commercialization and potential for cost reductions in the hydrogen technology

Even though the electrolyzer technology using water electrolysis used for producing hydrogen has shown promise, this technology still face several challenges (Hosseini and Wahid, 2016). The main issue is the high cost. Overcoming this issue related to PEM electrolysis, have been highlighted since the first studies were conducted in the early 1970's (see for instance Russell et al., 1973). There has, however, been done relatively few studies in the following years, partly making the issue still unresolved. Carmo et al. (2013) points to the need to reduce, or substitute, the use of expensive catalysts consisting of platinum, and also increase the utilization of these catalysts (Carmo et al., 2013). According to Hosseini and Wahid (2016), this metal "makes the process [of water electrolysis for producing hydrogen] non-economic" (Hosseini and Wahid, 2016, p. 853). Not only is the cost of platinum high, the reserves available for mining are also considered quite limited (Sealy, 2008). Hence, to eliminate such a precious metal in water electrolysis process, the utilization of, for example nanomaterial, has attracted attention (Hosseini and Wahid, 2016). Further, there is pointed to the importance to develop low cost current collectors and separator plates, and also improve the overall membrane structure (ibid.). Another main issue for the electrolyzers, is to reduce the energy consumption of water electrolysis (Wang et al., 2014).

The fuel cells on the market today, is still very much a 'work in progress', and face several drawbacks. Fuel cells does not work very well in temperatures below 0 °C, and they are in addition, not as durable as an ICE (MIT, 2017). In addition, the storage of hydrogen in the FCEVs faces problems. The tanks are larger, heavier and more expensive than those of a conventional vehicle. This is partly because they are fabricated using carbon fiber around a metal liner, a high-tech construction that is required by the fact that hydrogen fuel needs to be compressed up to 700 atmospheres (The Economist, 2017) for achieving a satisfying range. However, many of these problems are by some thought to be overcome "in due course" (The Economist, 2017).

The cost of the fuel cell can be divided into three parts: (i) the physical material and components, (ii) labor (design and fabrication), and (iii) the capital cost of the manufacturing equipment used (Marcinkoski et al., 2011). The two latter can potentially be reduced through mass-manufacturing, while the former can be reduced through technological development, potentially stemming from increased learning and experience.

The fuel cells also use platinum as a catalyst, in the same way as in the electrolyzer technology. And while some argue that the lead platinum has is likely to just increase in the future due to limitations other metals face compared to platinum (see for instance Holton and Stevenson, 2013), others claim to have discovered an inexpensive and easily produced metal-free catalysts that performs *even better* than platinum in fuel cells (Jeon et al., 2013). Others again, try to develop ways to use the platinum more efficiently. For example, Lindahl et al. (2017) points to a new type of nanocatalyst that can reduce the amount of platinum needed for a fuel cell by about 70%. The amount of platinum required would then be similar to what is used in an ordinary ICE car (ibid.). So even though there are several challenging aspects related to the cost of the platinum-use, this has been reduced in later years. As an example: today's fuel cell stacks[6] need only 10 grams of platinum compared to 29 grams in 2015 (The Economist, 2017).

Another important drawback for the fuel cell technology is the economics of transporting and dispensing the fuel (The Economist, 2017), i.e. the infrastructure for hydrogen. This is in part due to the fact that the fuel cell requires pure hydrogen as a fuel, which in turn means that it needs well developed infrastructure for production, distribution and storage of the hydrogen (Campillo et al., 2017). This is related to the well known *chicken-and-egg* issue, described in this context by Stolzenburg et al. (2009) as "no hydrogen infrastructure ... no demand for hydrogen vehicles", and "no hydrogen vehicles, therefore, no incentive to build a hydrogen infrastructure" (Stolzenburg et al., 2009, p. 7115). A solution to this challenge would, according to (Dunn, 2002), require "hundreds of billions of dollars" (Dunn, 2002, p. 237). However, The Coalition Study (2009)[7] stated that "prior

[6] As a single fuel cell delivers little electricity on its own, in FCEVs, the fuel cells are placed in *stacks*.

[7] Following McDowall (2012): "This report is frequently referred to as if the author were the consultants McKinsey and Company, who facilitated the report with a large number of other firms and organizations. The report was anonymously authored. We refer to it henceforth as the "Coalition Study". This approach

to 2030 is almost completely determined by the higher purchase price, not by the cost of the hydrogen infrastructure", and further assumed the cost of the infrastructure to only be 5% av the Total Cost of Ownership (TCO)[8] for the FCEVs. This again implies that the infrastructure challenge many point to, need not be too severe. The cheapest way to produce hydrogen is in large quantities at a central plant, before distributing it with special tanker lorries or by pipelines (The Economist, 2017). The hydrogen could in fact also be produced *on site* at the filling stations, which clearly will reduce the infrastructure cost (ibid.). But, because of the small scale production, the cost of producing the hydrogen is higher. In this thesis it will nevertheless be assumed that the hydrogen will be produced by electrolyzers *on site* at the filling stations (to be elaborated in section 4).

To sum up, the main challenges that needs to be addressed before the technology reaches a high market share, is primarily the high cost of both the electrolyzer technology and the fuel cell. This can potentially be solved by increasing the production experience, which in turn increases the learning and experience. Further, the lack of necessary infrastructure for refueling could hinder the commercialization, but this is disregarded in this thesis. As highlighted, the production on site will clearly reduce this cost.[9]

2.2 Battery technology for BEV

A battery is an electrochemical cell that transforms chemical energy to electrical energy (Pollet et al., 2012). It consists of an anode and a cathode which is separated by an electrolyte (ibid.), similar to the electrolyzer and fuel cell described in section 2.1. However, where the fuel cell produces electricity from an external source, i.e. hydrogen, a battery makes the electricity from energy stored inside the battery. It is the chemical reaction between the anode and cathode on one side, and the electrolyte on the other, that generates the direct current (Larminie and Lowry, 2012). This chemical reaction can be reversed for recharging the batteries (ibid.).

The two most used batteries for electric vehicles are lithium-ion (Li-ion) and nickel metal hydride (NiMH) (Pollet et al., 2012). The latter is mostly used in hybrid vehicles

will also be used in the remainder of this thesis.

[8]The TCO describes all the costs of the vehicle during its lifetime.

[9]In other words, the infrastructure cost will then mainly stem from the establishment of filling stations suitable for hydrogen. It is here often thought that the same filling stations used for fossil fuel could be used, though with some modification.

and thus disregarded here, while Li-ion batteries are the preferred type for BEVs. In a Li-ion battery, lithium in the anode is ionised and emitted to the electrolyte, where it moves through a separator to the cathode (Larminie and Lowry, 2012). Here electrons are released from the anode, making the electric current (ibid.). These batteries are attractive due to their high energy density per unit mass. These batteries have for example three times the energy density as the NiMH batteries (Catenacci et al., 2013). Another advantage is the relative cost compared to other types of batteries (Amirault et al., 2009), and is also preferred because of the relatively long life time (Campillo et al., 2017).

2.2.1 Barriers to commercialization and potential for cost reductions in the BEV technology

In the later years, the sale of BEVs have increased rapidly, and there are more and more electric vehicles on European roads (EEA, 2016*a*). However, they represent just 1.2% of all new cars that was sold in the EU in 2015 (ibid.). There are several reasons why the diffusion into the transport market is relatively slow. The major challenges for BEVs includes the cost of the Li-ion batteries, the size and weight, and also the durability of the battery (MIT, 2017). Further, the lower driving range compared to an ICE and FCEV car, makes the commercialization more difficult. The range is also sensitive to ambient temperature, which could reduce the battery energy (ibid.). Another important drawback of the BEV is the charging time which is several hours, and even fast charging takes significantly more time than for a FCEV or an ICE car (Greaker and Kristoffersen, 2017). The batteries are also complicated by the fact that the "battery systems are not sufficiently durable to have the same overall life as the vehicle itself" (McDowall, 2012). This is in contrast to the automotive fuel cell system and the electric drive system.

Following Egbue and Long (2012), another obstacle that need to be overcome before a widespread adoption of battery electric vehicles takes place, is that consumers often resist new technologies that are yet to be proved viable.[10] They also highlighted the need for policy intervention, which will be investigated in more detail in the model introduced below.

Bloomberg New Energy Finance analysed in 2017 the main factors that are expected to drive the diffusion of EVs in the future. These included growing consumer acceptance,

[10]This argument can of course also be used against the fuel cell technology described in section 2.1.

increased EV commitments from automakers, and also further falling Li-ion battery prices Bloomberg New Energy Finance (2017). Especially the latter can be due to increased learning and experience, following the approach in this thesis. In addition, the increased commitment can also be seen as potentially fostering experience.

To sum up, following the fact that the main difference between a BEV and conventional ICE vehicle lies in the power-train, more specifically, the battery, this is where the potential is biggest to reduce costs for making the BEV a viable alternative for the consumers (Nykvist and Nilsson, 2015). As can be seen from the reduction in the price of Li-ion batteries between 2010 and 2015, where the price dropped from $1000 per kilowatt-hour of storage, to $350 (The Economist, 2017), this follows the conclusion from Gaines and Cuenca (2000), where they underlined the large potential for cost reductions in this technology. With the reduced costs, some now believes that the technology has matured sufficiently so that future cost reductions will come in small steps, instead of what has been the case for the past two decades (The Economist, 2017).

3 Literature review

As the approach used in this thesis follows the experience curve methodology, the following section will present the basic idea and concepts behind the experience curves through a literature review. Following this, some evidence for experience curves is shown, especially related to battery and fuel cell technologies, in addition to other research using the experience curve approach.

3.1 Learning and experience curves

The idea behind learning curves was first formalized by Wright (1936). He found a negative relationship between the different inputs of production (as a function of cumulative production) and the costs of producing the commodity (OECD & IEA, 2000). One can think of this as the more you produce, the more you learn, which in turn reduces the costs for future production. This could be from increased efficiency, less errors, etc.. This will be elaborated in section 3.1.1. Wright plotted this relationship, which in turn resulted in lines with different, but negative, inclination. These curves became known as learning curves, which in sum reflects how the cost of producing a commodity is dependent on the relationship between single inputs and cumulative production of the commodity.[11]

While learning curves relates to the costs from specific inputs and is typically said to represent *learning-by-doing* (LBD), *experience curves* on the other hand, focuses on the *total* costs and how this is affected by cumulative production (Boston Consulting Group, 1968). It thus differs from the learning curves in that the sources of the cost reductions are much wider in an experience curve approach, as highlighted by Hall and Howell (1985). In the rest of the thesis, the terms *learning* and *experience* will be used somewhat intertwined as the model below does not distinguish specifically between different inputs.

Experience curves can be a powerful tool to examine how the development of a new technology has been. At the same time, it can give some indication of how future cost of this technology may evolve (Greaker and Sagen, 2008). This makes it a fruitful approach in this thesis, as the model introduced in Section 4 predicts future costs for the two technologies exposed to learning. The experience curve is often stated this (ibid.):

$$c_i = c_o x(t)^{-E} \tag{1}$$

where c_i is the unit cost, $x(t)$ is the accumulated production at time t, while c_o and E are positive parameters, and where c_0 is the cost per unit when accumulated production is equal to one, i.e. the costs for the first unit produced, and E represents the speed of the experience process, in that the higher the E, the more rapid the costs per unit will decrease as accumulated output increases.

An experience curve does not give a clear intuitive interpretation, so the *progress ratio* (PR) is often put forward. The PR expresses the reduction in unit costs when the accumulated production is doubled Bye et al. (2002), and is formally expressed as:

$$PR = \frac{c_0[2x(t)]^{-E}}{c_o[x(t)]^{-E}} = 2^{-E} \tag{2}$$

For example, if the PR is 0.7 then the unit costs will be 70% of the initial cost after a doubling of the accumulated production.

Closely connected to the PR, is the *learning rate*, which is simply $1 - PR$. In other words, a learning rate of 0.3 is the same as stating that the unit costs will be 30% lower every time the production is doubled (Bye et al., 2002).

[11] So formally it is the experience curves that is analyzed, but as this also include learning, this term will be used as well.

3.1.1 Main mechanisms behind experience curves

The literature points to several different mechanisms that lies behind the experience curves (see for instance Kahouli-Brahmi, 2008; Mayer et al., 2012; OECD & IEA, 2000; or Greaker and Sagen, 2008). First, repetitive manufacturing tasks leads to efficiency and improvement of the production process. This is in essence what Arrow (1962) labeled *learning-by-doing* (LBD). Second, experience can also be a driver for research and development (R&D) within the producing firms, which in turn can reduce the cost further - often referred to as process innovation (Greaker and Sagen, 2008), or *learning-by-researching* (Cohen and Levinthal, 1989). This mechanism has been debated whether or not it should be included in the experience curve, or that the effect of R&D activities should be isolated from the 'real' learning, or experience, effect. A third mechanism is the so-called *learning-by-using*, a concept introduced by Rosenberg (1982). Here, the feedback from the users of the product is the driver behind the increased experience. In other words, there is established a relationship between the internal and external surroundings of the firm (Kahouli-Brahmi, 2008), a distinction that will be elaborated below. In addition, there could be inter-industry spillovers in the experience process (Greaker and Sagen, 2008), related to what other firms in the industry and competitors do (Malerba, 1992). Fifth, *learning-by-interacting* (Kahouli-Brahmi, 2008) is interaction with either upstream or downstream sources of knowledge, like suppliers or the cooperation with other firms in the industry (Malerba, 1992). Finally, *economies of scale* usually emerge when output increases, and this is by some considered a learning effect that takes place at the mass production stage (Mayer et al., 2012). However, others argue that this is only a pure scale effect, and hence should not be interpreted as an experience effect (Greaker and Sagen, 2008). Formally, scale effects are not the same as a learning effect, but it is often problematic to separate these two phenomena (Kahouli-Brahmi, 2008). Thus, in the model presented below, there is made no distinction between scale effects and learning effects. It is important to have in mind that the learning effect then could be overestimated, an issue that will be discussed in Section 6 below.

Another distinction when it comes to learning, is the divide between *internal* and *external* learning (Malerba, 1992). Internal learning stems directly from a firm's own activity in areas such as production or R&D . External learning is based on knowledge from several different sources *outside* the firms own production, like other firms in the industry, suppliers or users, or from new technology developed by e.g. research centers or universities (Malerba, 1992; Kessler et al., 2000).

The following section will present evidence for experience curves found in the battery and hydrogen technology.

3.2 Research using the experience curve methodology for battery and hydrogen technology

Nykvist and Nilsson (2015) investigates how the cost of the Li-ion battery has developed, which was pointed to above as the dominating battery for the BEVs. They find that the cost is coming down, though there are relative large uncertainties in the magnitude of this reduction. Industry wide cost estimates declined with about 14% from 2007-2014, while the battery packs used by BEV manufacturers have had an annual decline of 8%. The learning rates Nykvist and Nilsson (2015) find is between 6% and 9%. They go on to anticipate that the cost will continue to decline.

Schoots et al. (2008) uses cost data observed from 1940 to 2007, and consider, amongst other, the technology of water electrolysis. They find only limited learning, and in addition, no cost reductions in the overall hydrogen production process, while the learning rate related to the investment cost of water electrolysis is $18 \pm 13\%$, in other words, there could actually be quite the learning effect for this investment cost, but it could not be stated with certainty. The authors also underline that the overall costs of using hydrogen will critically be determined by the costs of fuel cells, thus pointing to a relationship between the electrolyzer technology and the fuel cell.

The same authors published another paper, with a clearer result a few years later (Schoots et al., 2010), but now they analyzed past *fuel cell* cost reductions for both the global market and the individual manufacturers, and also determined learning curves for different types of fuel cells, among those the PEMFC. The analysis of was built on data between 1995 and 2006 and the fuel cell technology was characterized by a learning rate of 21%, i.e. a more robust result than what they found for the hydrogen production. from the paper in 2008. Further, following McDowall (2012), even with uncertain estimates of learning curves for this technology, "it would be possible to adopt the historical learning rates identified by Schoots et al. (2010) for future fuel cell and hydrogen production technology learning". This gives us an indication that the estimates found here could be relevant to use in the model when the simulations are done in section 5 below.

The traditional one-factor experience curve approach is defined as an approach "based on a univariate relationship between the unit cost of a product and the respective cumulative production volume" (Mayer et al., 2012, p. 14464). A two-factor approach in contrast, tries to single out 'R&D activities' from the more general experience, to explain the cost reductions. This two-factor approach is used in Mayer et al. (2012), where they investigated the cost reductions for both a PEM fuel cell stack and two types of Li-ion batteries. They do so by introducing a variable consisting of cumulative published patents as a proxy for R&D activities, to indicate the intensity of such types of activities. With the one-factor approach, a general experience rate for the fuel cell stack was calculated to be 22%, while in the case of a two-factor model, this number was 13%, but now with an additional 20% for the "R&D-based effect". For the Li-ion battery case in general[12], for the one-factor case, the learning rate is estimated to be 14% for the total experience effect, while this general experience effect is only 8% in the two-factor case, while 27% for the R&D-based experience effect. However, there is a very high degree of correlation between the two independent variables as one would expect, which gives a problem with multicollinearity. This is a potentially big problem for the results, but the results still gives us an indication of possible learning rates for both the hydrogen and battery technologies which is relevant for the simulations of the theoretical model presented below.

Tsuchiya and Kobayashi (2004) analyzes the cost *structure* of the fuel cell stack, using a learning curve approach, which means that different parts of the fuel cells are examined separately. This includes the cost of electrodes, platinum (the catalyst), the proton exchange membrane (PEM), bipolar plates (which works as electric conducting materials and impermeable walls), peripherals (include plastic frame, end plates and thrust bolts), and finally the assembly cost (the cost of putting it all together). Tsuchiya and Kobayashi (2004) test nine different scenarios, the results varying from 15$/kW to 145$/kW for the fuel cell stack in 2020. For the former estimate, the cost reduction reached the cost floor for several of the components. The lowest cost found is critically dependent on an assumption of mass production, but if this is the case, the results shows that the fuel cell stack could be competitive to the internal combustion engine. This could point to the

[12]There is in (Mayer et al., 2012) mad a distinction between high energy and high power Li-ion batteries, when estimating different cost reductions.

need of stimulating this technology for it to be competitive, as will be discussed below.

Sano et al. (2005) studies cost-effective technological options for stabilizing different CO_2 levels measured by parts per million by volume (ppmv). Here, FCEVs[13] are considered to follow a learning-by-doing process, and the authors assume a learning rate for these vehicles of 20%. They report in their sensitivity analysis that an even higher learning rate does not accelerate the use of FCEVs further, as the assumed learning rate is at an already high level. This result is interesting for the simulations below, as many of the simulations below will be done with a relatively high learning rate in the FCEV case.

Anandarajah et al. (2013) develop long-term scenarios for future costs for both fuel cell and electric vehicles, by implementing global technology learning. They do so in a model that takes the view of a global social planner with perfect foresight, the same as the theoretical approach below, to identify the least cost abatement path. The initial costs are the same as those set out in The Coalition Study (2009), while the floor costs are based on Tsuchiya and Kobayashi (2004). The results in Anandarajah et al. (2013), suggests that both hydrogen and electric vehicles should be used in all scenarios. This is interesting to have in mind when the result of the simulations in the thesis below are presented. The authors suggests that this is partly reflected by the fact that they share many of the same components, so that reduction in the cost of one, often will lead to reduction in the other as well. For instance, batteries are present in both BEVs and FCEVs. Thus, this argument could underline the existence of a synergy effect. In sum, the results from this study shows that both "hydrogen and electricity can play a critical role to decarbonize the transport sector" (Anandarajah et al., 2013, p. 3419). Following this, the research question in this thesis is relevant as it will shed more light on the use of hydrogen and battery in transport, and also whether the results will combine the use of both battery and hydrogen technology, or just one of them.

Table 1 (taken from McDowall, 2012) sums up the literature on learning rates for hydrogen technology, and especially for fuel cells:

[13] I.e. the cost of the whole vehicle and not just the fuel cells.

Table 1: Learning in studies of hydrogen vehicles

Summary table		
Study	Object of learning	Progress ratio
Gül et al. (2009)	Fuel cell	0,85
Gül et al. (2009)	Fuel cell battery system	0,85
ETP2008	"Fuel cell drive systems"	0,78
Sano et al. (2005)	Fuel cell	0,8
Sano et al. (2005)	Hydrogen tank	0,9
Feber et al.	Fuel cell	0,82
Matsson & Wene (1997)	Fuel cell	0,87
Gritsevskyi & Nakicenovic (2000)	Fuel cell	0,8
Schwoon (2008)	Fuel cell drive system	0,85
Seebregts et al. (1998)	Fuel cell vehicle	0,82
Coalition Study (2009)	Fuel cell	0,85
Coalition Study (2009)	Hydrogen tank	0,85
Coalition Study (2009)	Fuel cell system periphery	0,85
HyWays (2008)	Fuel cell system, moderate scenario, first ten years	0,82
HyWays (2008)	Fuel cell system, moderate scenario, after ten years	0,92
HyWays (2008)	Fuel cell system, optimistic scenario, first ten years	0,80
HyWays (2008)	Fuel cell system, optimistic scenario, after ten years	0,90
HyWays (2008)	Hydrogen tank	0,90
HyWays (2008)	Electric motor and controller	0,90
Sclecht (2003)	Fuel cell system and powertrain	0.8
Sclecht (2003)	Fuel cell system and powertrain	0.7
Sclecht (2003)	Fuel cell system and powertrain	0.6
Krzyanowski (2008)	Fuel cell system	0.8-0.95

As we know from above, the learning rates are '1 - the Progress Ratio', so as given in Table 1, these rates are mainly in the range of 15-20% (the average PR of all rates in Table 1 is 83%, which implies a learning rate of 17%). In the simulations below, the baseline scenario will take a learning rate of 20% as the outset, i.e. a somewhat optimistic rate according to Table 1, but in line with Schoots et al. (2010).

3.3 Total Cost of Ownership forecasts for the technologies of interest

Other research that investigates the future cost of the different technologies of interest, is Le Duigou and Smatti (2014). They do, however, not use learning curves like the model developed in this thesis, introduced in 4, but their findings and initial estimates are still very interesting as it sheds light over possible cost reductions for the battery and fuel cell technology. In the simulations below, some of the costs used by Le Duigou and Smatti (2014) will be taken as an outset when the model in section 4 is calibrated. They further use the total cost of ownership in the period from 2012 to 2030. Some of the estimates used in section 5, will also be based on a TCO assessment for the different technologies. In Le Duigou and Smatti (2014), the estimates is based on forecasts of the most important costs involved in the TCO for ICEs, FCEVs, and BEVs, including energy (fuel) prices, driving distance, batteries and fuel cell costs. The cost projections they use are based on a literature survey. For the FCEVs, the cost development covers the hydrogen tank and fuel cell components (among them the fuel cell stack itself). They further assume that the range of the BEVs will increase throughout the time period they are looking at, but "will still remain significantly lower than that of a conventional vehicle" (Le Duigou and Smatti, 2014, p. 5). This is in line with the assumptions made in this thesis, which is introduced in the section about the theoretical model.

Le Duigou and Smatti (2014) concludes that both BEVs and FCEVs are almost cost-effective compared to ICEs between 2020 and 2030, and are fully competitive in 2030. This is also interesting for the simulations below, to see if the results differ from this, or is in line with these findings, especially since some of the values and estimates used by Le Duigou and Smatti (2014) will be used as an outset for the model below.

3.4 Learning outside the battery and hydrogen technologies

As the model developed in this thesis is inspired by Kverndokk and Rosendahl (2007), this paper will be now be introduced.

Kverndokk and Rosendahl (2007) examines how the optimal combination of carbon taxes and a subsidy to an existing carbon-free energy technology should be, analyzed in a theoretical model. They use a dynamic equilibrium model with learning by doing, including a trade-off between carbon taxes and technology subsidies in order to comply with a carbon constraint. Further, it is a partial equilibrium model, in that there is a fixed present value of income that a social planner can allocate across time, to either electric or non-electric consumption. The model introduced below, is loosely inspired by this model, and the social planner approach will also be used there, but instead of electric and non-electric consumption, the model will look at transport and non-transport consumption.

In Kverndokk and Rosendahl (2007), the electric goods can be produced by three different energy technologies, namely a *defender (DEF), a challenger (CHL) and an advanced (ADV)* technology. The DEF technology is todays existing technology, which is a predominantly fossil mix of technologies, while CHL is the initial challenger technology, with high initial cost, but subject to endogenous learning that will lower the cost in the future. The latter technology is thought to become available some time during this century, with lower cost and also subject to learning-by-doing. Both the CHL and the ADV technology are assumed to be carbon-free, and the learning potential for these two are assumed to possibly halve their unit investment costs. These costs are in part determined by an initial learning cost coefficient, combined with a learning parameter. The next period accumulated experience is the sum of present accumulated experience. Kverndokk and Rosendahl (2007) further involves a cap on emissions from the electricity sector that should not be exceeded.

The results by Kverndokk and Rosendahl (2007) show, in general, that the optimal subsidy rate for the CHL technology should fall over time. This rate is optimal to set lower if the learning potential of this technology is lower than what is originally assumed, but the rate will still fall over time. In addition, the time profile of this subsidy rate is almost entirely determined by the learning potential for this technology. Another important conclusion is that the greatest return to learning, and hence the highest optimal subsidy, occurs at the time a technology is first introduced, while this return falls significantly over the following decades. This result will be compared to the results in the next section.

4 A theoretical model with learning

In this section a stylized bottom-up model[14] is presented. This is inspired by the model by Kverndokk and Rosendahl (2007), presented in the previous section. While Kverndokk and Rosendahl (2007) considered subsidies on electric energy technologies in discrete time, here consumption (and indirectly, production) of different transport technologies in continuous time are decided, using optimal control theory. The model developed here uses partly the same logic as Kverndokk and Rosendahl (2007) do, with fossil technology as an analogy to the defender type, battery technology as the initial challenger, and hydrogen technology as the advanced technology. But where Kverndokk and Rosendahl (2007) assume the ADV technology to might become available some time in the future, the hydrogen technology is in the model presented here, considered to already be present, with a high initial cost. To be clear from the outset, the focus in the model is mainly directed towards the transport technologies *in relation* to each other, and less focus will be on the transport relative to the economy as a whole.

The model describes the transport sector in the EU, and considers all *road transport*. Thus shipping, aviation and rail transport is left out. This is done partly for simplicity, but also from the fact that, from an environmental point of view, shipping only accounts for about 2.5% of global greenhouse gas emission (European Commision, 2017*b*), rails in many cases are electrified through a railway electrification system, while aviation is, at least partly, included in EU ETS, i.e. without use of batteries or hydrogen. In addition, aviation "only" accounts for around 3% of the EU's GHG emissions (European Commision, 2017*a*), compared to road transport's 20% (European Commision, 2017*c*). As the thesis looks at all road transport, the transport considered here includes both transport of goods and transport of people (both public and private).

The potential cost reduction for the different technologies is considered to be due to learning and experience. This is the main reason why the EU is investigated, and

[14] A regular bottom-up model focus on substitutability of individual technologies and their relative costs, while top-down explores market interactions within the whole economy, with little focus on technological details (van Vuuren et al., 2009).

not, for example, Norway. As the markets for battery and hydrogen technology is bigger in the EU, there is larger potential for learning and experience, in both hydrogen and battery technology, which is the technologies considered with learning potential. Further, it is assumed that all hydrogen is produced by electrolysis. As the electricity used in this process is generated by power stations that are included in the EU ETS, the use of hydrogen is seen here as a pure source of emission cuts. The same reasoning is done for the battery technology, so that both technologies are considered *clean* in contrast to the fossil technology.

Following the approach of Le Duigou and Smatti (2014), it is assumed for simplicity that the infrastructure for both BEVs and FCEVs are in place. As the hydrogen is also assumed to be generated *on site* at the fuel station, this makes the former assumption more valid as much of the infrastructure cost will be disregarded as the hydrogen is produced at the stations. Further, the producing firms are assumed to be myopic.

The social planner in this model is subject to a budget constraint:

$$\overline{M}(t) = \sum_{j} \Big((p_j(t) + \tau_j(t))x_j(t) \Big) + C(t) \tag{3}$$

where $\overline{M}(t)$ shows the available income for the planner at point in time t (this could for instance be thought of as the total GDP in the EU), $p_j(t)$ is the price of transport goods from technology j at time t, where $j \epsilon \big\{f = fossil, h = hydrogen, b = battery\big\}$, while $x_j(t)$ is the consumption of road transport from technology j. $\tau(t)_j$ is the tax from consuming transport from technology j, where $\tau(t)_j = 0$ for $j = \{h, b\}$. In other words, since there is assumed zero emissions from the use of hydrogen and battery technology, only the fossil technology is subject to a tax, as it is a tax on emissions. This could for instance have come about due to a climate treaty, that puts a 'ceiling' on all EU emissions. It is also assumed that this tax will increase with a factor ϕ per year. This is because the ceiling on total emissions will be lowered in the future as the EU have stated to reduce GHG emissions with 40% by 2030 and 80% in 2050, relative to 1990 levels. The tax will in this setting thus be equal the alternative cost of reducing emissions in other sectors. In contrast to Kverndokk & Rosendahl (2007), who explicitly assume a constraint on total carbon emissions, the approach here will be that if emission from transport is not lowered sufficiently, then there must be reductions in other sectors. Also, the cost of non-transport consumption is normalized to unity, so the alternative costs for the transport technologies will be what instead could be consumed of non-transportation goods, $C(t)$. $\overline{M}(t)$ is assumed to increase with $\gamma\%$ per year (to reflect the GDP metaphor).

Further, there is two state variables[15] of interest, $H_t(t)$, and $B_t(t)$, which represents the accumulated experience of hydrogen and battery technology, respectively. These state variables evolve over time relative to what is produced using these technologies, i.e. if using more hydrogen technology today, by increasing the control variable $x_h(t)$, the more experience you gain, and hence $H(t)$ will increase.

$$\frac{dH_t(t)}{dt} = \dot{H}_t(t) = h(x_h(t)) = x_h(t) \tag{4}$$

The same relationship holds for battery technology:

$$\frac{dB_t(t)}{dt} = \dot{B}_t(t) = b(x_b(t)) = x_b(t) \tag{5}$$

The state variables will affect the prices in the budget constraint in the following way:

$$p_h(t) = \bar{\omega}_h + \omega_h(0) \int_0^t x_h(t)dt = \bar{\omega}_h + \omega_h(0) \int_0^t \dot{H}_t(t)dt = \bar{\omega}_h + \omega_h(0) H_t(t)^{-\alpha_h} \tag{6}$$

for the hydrogen case, and

$$p_b(t) = \bar{\omega}_b + \omega_b(0) \int_0^t x_b(t)dt = \bar{\omega}_b + \omega_b(0) \int_0^t \dot{B}_t(t)dt = \bar{\omega}_b + \omega_b(0) B_t(t)^{-\alpha_b} \tag{7}$$

for the battery technology.

In (6) and (7), $\bar{\omega}_h$ and $\bar{\omega}_b$ is the constant unit production cost for hydrogen and battery technology (could also be viewed as a "cost floor" in that the cost cannot go towards zero even though the learning is massive), $\omega_h(0)$ and $\omega_b(0)$ is the cost of the unit produced with the two clean technologies at time *0*, i.e. the initial cost, and α_h and α_b is the learning parameter, which shows the speed of the experience process. The higher the α, the faster will cost per unit decrease with accumulated output. The integral from *0* to *t*, reflects all the production from either hydrogen or battery technology, up to the point we are looking at, in other words, the accumulated production of the technology technology. In sum, we see that the cost, and hence the price, becomes lower over time (as long as the technology is used) due to the learning effects.

As a social planner problem, the price is reflected in the *total* cost of using these technologies. These costs include both capital and user costs. This is done for simplicity,

[15] Variables that characterizes the 'mathematical' state in a dynamic setting (Sydsæter et al., 2002)

and due to the fact that the capital costs easily can be transformed into a yearly cost if one knows the lifetime of the capital and the corresponding interest rate, before adding it to the user cost. The total user cost (or TCO as defined above) consists of fuel prices (fossil fuel prices, electricity prices, hydrogen prices), maintenance expenditures, how long lifetime the vehicle has, the purchasing price, and so on.

In contrast to the emission free technologies, the price of fossil fuel technology, and thus the cost, is assumed constant:

$$p_f(t) = \bar{p}_f \tag{8}$$

The constant price reflects an assumption of no learning potential for this technology. In other words, there is no potential to reduce future costs of this technology. This is obviously a simplification as one would also expect learning potential in this technology even though the technology has matured. Still, it could for instance be argued that since this technology depends on a non-renewable resource, the less resources left in the ground due to previous extraction, the costlier it will be to extract the remaining resource. This could be the case because there is need to search new places with the possible lack of sufficient infrastructure, or that to find the resource the drilling much be deeper than before. This could outweigh the lower cost potential, and result in a constant cost over time. In contrast to a non-renewable resource like fossil, both Li-ion batteries and platinum used in fuel cells are for instance possible to recycle (see for example Xu et al., 2008 and Hagelüken, 2012).

The consumers in this model receive utility from either of two goods, transportation and 'all other goods', in the following way:

$$u\big(T(t), C(t)\big) = \Big[\theta T(t)^\rho + (1-\theta)C(t)^\rho\Big]^{1/\rho} \tag{9}$$

where $\theta T(t) \geq 0 \; \forall t$, $(1-\theta)C(t) \geq 0 \; \forall t$, so that $u(0,0) = 0$, $u' > 0$, and $u'' < 0$ (as long as $\rho \leq 1$). θ is a share parameter[16], $T(t)$ is transport consumed at time t, $C(t)$ is the amount of non-transportation goods that is consumed at the same time, while ρ is the substitution parameter between these two types of goods. Transport and non-transport goods are considered to be complements, which is the same as saying that $\rho < 1$[17] As

[16]In the simulation below this is assumed to be 0.2, which states that the share of transport in total utility, is weighted less than *all other* types of goods.

[17]This assumption will be further discussed in the next section.

it is clear from (9), this utility function is a constant elasticity of substitution-function (CES), so that the substitutability between transport goods and non-transport goods, is assumed to be constant.

Consumption of transport at time t, $T(t)$, is defined in the following manner:

$$T(t) = \Big[\big(x_f(t) + x_h(t)\big)^\eta + x_b(t)^\eta\Big]^{1/\eta} \tag{10}$$

where $x_j(t)$ is consumption from technology j, $j\epsilon\{f = fossil, h = hydrogen, b = battery\}$, at time t. η is the substitution parameter between fossil/hydrogen and battery. Also, evident from (9) and (10) is that we are looking at nested CES-functions. Fossil and hydrogen are here considered to be perfect substitutes. Hydrogen is more expensive than fossil, which makes fossil the preferred technology of these two today. The perfect substitutability assumption is based on similarities in end-use of both technologies for transport use. For both hydrogen cars and the standard internal combustion engine (ICE) car, the filling takes place at a station, the time to ill up the tank is relatively similar, and the range is more or less the same, as highlighted above. This is in contrast to BEVs, where the range is smaller in addition to the charging of the batteries, which may take several hours (see for instance Greaker and Kristoffersen, 2017). Even fast charging takes about 30 minutes (ibid.). For comparison, Le Duigou and Smatti (2014), states that the "ranges of FCEVs are significantly higher than those of BEVs, and hydrogen refueling is feasible quickly in stations similar to the present ones" (Le Duigou and Smatti, 2014, p. 7). The range for BEVs is also vulnerable to extra weight, like car trailers or motorhomes, i.e. heavy goods vehicles (HGV) used for both freight transport and recreational purposes. In this segment, hydrogen is generally assumed to have a higher potential than the BEVs, which again reinforces the perfect substitutability assumption the model is based on (see for example Campillo et al., 2017).

The social planners object, is then to maximize:

$$\max_{T(t),C(t)} \int_0^\infty e^{-rt} u(T(t), C(t))dt \tag{11}$$

Here, r is an exogenous positive discount rate, and $C(t)$ and $T(t)$ are the control variables for the planner (it is in fact $x_f(t)$, $x_h(t)$, and $x_b(t)$ that are the 'true' control variables in that it is those variables the government decides at each point in time, while $T(t)$ is an aggregate of the three x's and $C(t)$ is given by the budget constraint (3) above when $x_f(t)$, $x_h(t)$, and $x_b(t)$ is decided).

The initial experience in the two 'learning'-technologies is given positive values, as there are some experience of both technologies (as shown above):

$$H_t(0) = H_{t_0} > 0 \tag{12}$$

$$B_t(0) = B_{t_0} > 0 \tag{13}$$

We also have the following terminal conditions for the state variables of interest:

$$\lim_{t\to\infty} H_t(t) \geq 0 \tag{14}$$

$$\lim_{t\to\infty} B_t(t) \geq 0 \tag{15}$$

which states that there is not possible to reach 'negative experience' for the two technologies. From (12) and (13) we know that the initial experience is positive, and assuming that experience cannot be lost once attained, then $H_t(t)$ and $B_t(t)$ will hold for all t, and the terminal conditions will be satisfied.

The current value Hamiltonian (skipping time notation), H^{CV}, following from the above, will then be:

$$H^{CV} = \Big[\theta T^{\rho} + (1-\theta)C^{\rho}\Big]^{\frac{1}{\rho}} + \lambda_h \dot{H}_t + \lambda_b \dot{B}_t \tag{16}$$

or equivalently:

$$H^{CV} = \Big[\theta T^{\rho} + (1-\theta)C^{\rho}\Big]^{\frac{1}{\rho}} + \lambda_h x_h + \lambda_b x_b \tag{17}$$

where λ_h and λ_b are the co-state variables. These will always be non-negative as more of the state variables (experience) is considered 'good' (Hoel, 2016). These variables are also often referred to as the (current) shadow value or shadow price, of the state variable. In other words, λ_h, for example, reflects the (current) value of a marginal increase in the experience for hydrogen technology. What is also clear, and somewhat obvious, from (17), is that the use of transport technologies gives direct utility in itself, while it affects the utility of non-transportation goods negative in that the more you use on transport, the less is left to be used on non-transport goods. The two clean technologies also increases utility through the stock variable, experience, in that it lowers the future costs of using these technologies when utilizing them today. Finally we know that the Hamiltonian is concave in (x_j, H_t, B_t) because it consists of a CES-part (which is concave as long as $\rho \leq 1$, $\theta \geq 0$, and $(1-\theta) \geq 0$) and two linear terms.

4.1 First order conditions

As the optimal combination of the three control variables, maximizes the current value Hamiltonian, i.e. (17), we start by differentiating (14) with respect to the control variable x_f. Applying the chain rule, we get the following first order condition (FOC):

$$\frac{dH}{dx_f} = \left[\theta T^\rho + (1-\theta)C^\rho\right]^{\frac{1-\rho}{\rho}} \left(\theta T^{\rho-1}\frac{dT}{dx_f} + (1-\theta)C^{\rho-1}\frac{dC}{dx_f}\right) = 0$$

by rearranging and dividing by the part inside the square brackets, we get:

$$\theta T^{\rho-1}\frac{dT}{dx_f} = -(1-\theta)C^{\rho-1}\frac{dC}{dx_f} \tag{18}$$

as $\frac{dT}{dx_f} > 0$ and $\frac{dC}{dx_f} < 0$, it follows that both sides are positive. Since there is no learning present, and hence no shadow values, the economic interpretation is relatively straightforward. The equation simply states that the marginal utility from transport that one gets from consuming fossil fuel technology, should equal the marginal utility gain of non-transportation goods if you instead used the same amount of your budget on these goods, when the two types of goods are weighted to their relative (utility) share. If this condition had not been satisfied, e.g. if the right hand (RHS) side were bigger than the left hand side (LHS), you would lose relatively less utility from non-transportation goods than you would gain utility from transport when increasing the transport consumption using fossil technology. This of course means that you would rather consume less transport and more of non-transportation goods.

For the hydrogen case, x_h, the FOC will also include a term with the shadow price of hydrogen experience[18]:

$$\frac{dH}{dx_h} = \left[\theta T^\rho + (1-\theta)C^\rho\right]^{\frac{1-\rho}{\rho}} \left(\theta T^{\rho-1}\frac{dT}{dx_h} + (1-\theta)C^{\rho-1}\frac{dC}{dx_h}\right) + \lambda_h = 0$$

$$\implies \theta T^{\rho-1}\frac{dT}{dx_h} + \left(\theta T^\rho + (1-\theta)C^\rho\right)^{\frac{\rho}{1-\rho}}\lambda_h = -(1-\theta)C^{\rho-1}\frac{dC}{dx_h} \tag{19}$$

Compared to (16), now there is also an additional positive term containing λ_h on the LHS. This reflects the additional value that exists due to the learning that is taking place when using hydrogen technology. Utility increases when consuming transport, but utility is also increased due to the lower future cost for hydrogen technology. This means that the

[18]See the Appendix for a step-by-step procedure.

planner would increase the consumption of hydrogen technology today relative to what would be the case if there were no learning in the technology.

The FOC for the battery technology:

$$\frac{dH}{dx_b} = 0 \implies \theta T^{\rho-1}\frac{dT}{dx_b} + \left(\theta T^{\rho} + (1-\theta)C^{\rho}\right)^{\frac{\rho}{1-\rho}}\lambda_b = -(1-\theta)C^{\rho-1}\frac{dC}{dx_b} \qquad (20)$$

The intuition here is the same as for (19), i.e. you want to consume transport from battery technology to the point where the marginal utility from this transport technology is equal to the utility you would derive if you instead used an additional resource on non-transportation goods. And, as was the case for hydrogen, the utility of consuming transport now stems from two sources, namely the transport itself, but also the reduced future cost.

Since the firms are assumed to be myopic, then a future cost reduction due to increased learning and experience, will not be taken into account by the firms themselves. This includes the whole term where λ_h and λ_b is included. If there had not been a social planner present, but rather decentralized decisions, this could have paved the way for a subsidy toward the two technologies where learning is present, so that the learning would be internalized by the firms. This will be discussed further in section 5.4, where this potential subsidy is plotted.

4.2 Costate equations

Further, to investigate the development of the shadow values of experience, there will be need for the following differential equations:

$$\dot{\lambda}_h(t) - r\lambda_h(t) = -H'_{H_t} \qquad (21)$$

Remembering that the price-term for both hydrogen and battery includes the state variables *H(t)* and *B(t)* from equation (6) and (7), gives the following costate equation for the hydrogen technology:

$$\dot{\lambda}_h(t) - r\lambda_h(t) = -\big(u(T(t), C(t))\big)^{\frac{1}{1-\rho}}(1-\theta)C(t)^{\rho-1}\frac{dC(t)}{dH(t)_t} \qquad (22)$$

where $\frac{dC}{dH_t} = \alpha_h \omega_{h_o} x_h H_t^{-(\alpha_h+1)}$.[19] For the battery experience:

$$\dot{\lambda}_b(t) - r\lambda_b(t) = -H'_{B_t}(t) \qquad (23)$$

[19]See the Appendix.

so that

$$\dot{\lambda}_b(t) - r\lambda_b(t) = -\big(u(T(t), C(t))\big)^{\frac{1}{1-\rho}}(1-\theta)C(t)^{\rho-1}\frac{dC(t)}{dB_t(t)} \tag{24}$$

where $\frac{dC}{dB_t(t)}\alpha_b\omega_{b_o}x_b(t)B_t(t)^{-(\alpha_b+1)})$. In addition, there is no need for a piecewise continuous function in (22) and (24), as the state variables will always be positive (Hoel, 2016).

Further, (22) and (24) can be rearranged so that we get the relative growth rate of the shadow prices, i.e. the λ's. by moving the r-terms to the RHS, inserting for $\frac{dC}{dH_t(t)}$ and $\frac{dC}{dB_t(t)}$, before dividing by λ_h and λ_b in (22) and (24) respectively:

$$\frac{\dot{\lambda}_h}{\lambda_h} = r - \frac{\big(u(T(t), C(t))\big)^{\frac{1}{1-\rho}}(1-\theta)C(t)^{\rho-1}\alpha_h\omega_{h_o}x_h(t)H_t(t)^{-(\alpha_h+1)}}{\lambda_h} \tag{25}$$

$$\frac{\dot{\lambda}_b}{\lambda_b} = r - \frac{\big(u(T(t), C(t))\big)^{\frac{1}{1-\rho}}(1-\theta)C(t)^{\rho-1}\alpha_b\omega_{b_o}x_b(t)B_t(t)^{-(\alpha_b+1)}}{\lambda_b} \tag{26}$$

From (19) and (20), we can get explicit expressions for λ_h[20] and λ_b, and insert these to (25) and (26) to get the following):

$$\frac{\dot{\lambda}_h}{\lambda_h} = r - \frac{\big(u(T(t), C(t))\big)^{\frac{1}{1-\rho}}(1-\theta)C(t)^{\rho-1}\alpha_h\omega_{h_o}x_h(t)H_t(t)^{-(\alpha_h+1)}}{\big(\theta T(t)^\rho + (1-\theta)C(t)^\rho\big)^{\frac{1-\rho}{\rho}}\big((1-\theta)C(t)^{\rho-1}p_h(t) - \theta T(t)^{\rho-1}\frac{dT}{dx_h}\big)} \tag{27}$$

and the same for battery:

$$\frac{\dot{\lambda}_b}{\lambda_b} = r - \frac{\big(u(T(t), C(t))\big)^{\frac{1}{1-\rho}}(1-\theta)C(t)^{\rho-1}\alpha_b\omega_{b_o}x_b(t)B_t(t)^{-(\alpha_b+1)}}{\big(\theta T(t)^\rho + (1-\theta)C(t)^\rho\big)^{\frac{1-\rho}{\rho}}\big((1-\theta)C(t)^{\rho-1}p_b(t) - \theta T(t)^{\rho-1}\frac{dT}{dx_b}\big)} \tag{28}$$

These equations are somewhat hard to interpret. However, there is reason to believe that the shadow value of the experience will be high in an initial phase, as the potential for learning is higher than it will be after the accumulated production reaches substantial levels. In other words, that the shadow price of experience should decline over time. This would be because as there is little experience in the initial phase, to double the cumulated output would require a quite small increase in production, and the learning rate will result in a high cost decline early on. As more experience are gained, the marginal value of experience will be smaller than before. If the costs for battery and hydrogen technology were sufficiently large, then the costs would reach the cost floor. Then there is no longer any possibility of reducing the cost further. This in turn would mean the marginal value

[20] See the Appendix.

of experience would be zero. This is in line with the findings of Kverndokk and Rosendahl (2007), where it was showed that the greatest return to learning was during the period where the technology was first introduced, before falling significantly over time.

The growth rate of the shadow values of experience for the two clean technologies (i.e. (27) and (28)), should possibly also be high to begin with, before starting to decline. This cannot however be stated with certainty based on (27) and (28), but in the simulations below building on this model[21], it will also be shown that this actually is the case here.

As the model does not give an indication of how the distribution of the technologies *in relation* to each other, this will now be investigated in the simulations.

5 Simulations

The former section introduced the theoretical model in continuous time. In this section, that case is transformed to discrete time, to make simulations. The rationale for making these simulations is to show how the model works in practice, and also what it suggests as an optimal consumption path of the different technologies in the future, given the estimates and parameters used.[22] The model is constructed in the same way as in the continuous case. For simplicity, we will now look at a 100-year time horizon, by selecting the control variables in twenty five-year periods.

5.1 Set-up of the model in discrete time

The model uses more or less the same notation as in the previous section. Where there are additional terms included, they are defined consecutively in the following. The maximization problem is further programmed in Excel[23] and solved using the Excel Solver add-in.

The maximization problem is now

$$\max_{T_t, C_t} \left(\sum_{t=0}^{100} \beta^t u(T_t, C_t) \right) \tag{29}$$

[21]The same model transformed to discrete time.

[22]It should be stressed that the values used for simulations serves, to some extent, an illustrative purpose of the model, and the scenarios presented does not claim to be a very good projection of the future.

[23]Hence the discrete time transformation.

where β is the discount factor, and the consumers still receive utility from either of two goods

$$u(T_t, C_t) = \Big[\theta(T_t)^\rho + (1-\theta)(C_t)^\rho\Big]^{1/\rho} \tag{30}$$

with the same notation as in the previous section. The transport is divided in the same manner as in the continuous case, with perfect substitutability between fossil and hydrogen technology:

$$T_t = \big((x_{ft} + x_{ht})^\eta + (x_{bt})^\eta\big)^{1/\eta} \tag{31}$$

The budget constraint is also still present:

$$\overline{M}_t = \big(p_{ft} + \tau_t\big)x_{ft} + p_{ht}x_{ht} + p_{bt}x_{bt} + C_t \tag{32}$$

where $\overline{M}(t)$ are assumed to increase with $\gamma\%$ per five-year period:

$$\overline{M}_{t+1} = \overline{M}_t * \gamma \tag{33}$$

The tax on emission also increases over time

$$\tau_{t+1} = \tau_t * \phi \tag{34}$$

where ϕ is the increase per five-year. Further, the experience for hydrogen and battery develops over time as:

$$H_{t+1} = x_{ht} \tag{35}$$

$$B_{t+1} = x_{bt} \tag{36}$$

The fossil technology's price is still treated constant:

$$p_{ft} = \bar{p_f} \tag{37}$$

while the price for the two learning technologies is dependent on the amount of learning and production:

$$p_{ht} = \bar{\omega}_h + \omega_{h0}\big(\sum_{t=0}^{t-1} x_{ht}\big)^{-\alpha_h} \tag{38}$$

for the hydrogen, and for the battery:

$$p_{bt} = \bar{\omega}_b + \omega_{b0}\big(\sum_{t=0}^{t-1} x_{bt}\big)^{-\alpha_b} \tag{39}$$

thus we see that the price for hydrogen and battery at a given point in time, are decided by the cumulative production *up to* the point where we look at the price, in other words, the production till *t-1*.

5.2 Assumptions and cost estimates

5.2.1 Cost estimates

The focus in this section will be on conventional passenger ICE vehicles to represent the fossil technology, an 'ordinary' FCEV will be a proxy for the hydrogen technology, while a 'regular' BEVs will describe the battery technology. In other words, the different cost estimates for the technologies are illustrated for these representative vehicles. For the two learning technologies, this choice is explained by the fact that battery and hydrogen technology are not much used in other vehicles, like heavy goods vehicles (HGV).

In Table 2 and 3, the estimates used for calculating the initial costs of the different transport technologies are presented, i.e. $\bar{p}_{ft}$, ω_{h0}, and ω_{b0}. The goal for calculating these costs are to get a realistic *relationship* of how the three technologies develop over the time horizon. In other words, it is the *share of fossil*, in the lowermost row in Table 3 below, that will be used as a starting point in the simulation. As there are uncertainties in many of the chosen values, the first step is trying to estimate a relationship between the three technologies that seems reasonable. Since the outset of the model is a problem for a social planner, then all cost needs to be included, excluding taxes, so that only objective alternative costs are considered. The TCO is estimated for one year, and even though the planner sets the control variables of transport in five-year periods, the scaling of these numbers does not alter the cost *relationship* between the technologies.

Table 2 shows the estimates for the yearly operating and maintenance cost:

Table 2: Operating and maintenance cost per year

	Fossil	FCEV	BEV	Unit
Fuel cost per km [24]	3.55	6.49	2.84	NOK
Yearly mileage per year	13 000	13 000	13 000	kilometer
Maintenance cost	6580	4700	4700	NOK
Insurance cost	6580	6580	6580	NOK
Sum	47 748	95 609	48 174	NOK

The average fuel price in Europe since 1980 is 0.98€/l (EEA, 2016*b*), i.e. 9.2 NOK[25]/l . The average tax rate on fuel is 0.54 as of 2013 (EEA, 2013) which yields 4.72 NOK per liter, and when assumed that an ICE uses 0.75l/km, the fuel cost per km will be 3.55 NOK. Additionally, and to the yearly mileage is considered to be 13 000km (following ADAC, 2015), and the liter per kilometer (figuratively speaking for the two clean technologies as it is actually price per kilowatt/hour) is also assumed equal[26]. It is further assumed a constant maintenance and investment cost over time.[27] This is also calculated on the basis of Le Duigou and Smatti (2014).[28] The former is slightly higher for an ICE than for the two others, due to the fact that the two latter have fewer rotating parts and also a higher share of low-maintenance components (see for instance Egbue and Long, 2012;Le Duigou and Smatti, 2014), while the latter is assumed equal for all three. Using the total operating and maintenance cost per year, we get the total user cost of the different vehicle types presented in Table 3.

[24]The same relationship between the three types as stated by Le Duigou and Smatti (2014) when they compared the price of ICE fuel, electricity and hydrogen, is used here. There hydrogen is about 40% more expensive than regular fuel for an ICE, while electricity is about 17% cheaper, all measured in kilowatt hour. This share are multiplied with the price per liter excluding tax, for fossil technology. For simplicity this relationship is also assumed for FCEVs and BEVs.

[25]With an exchange rate of 9.4

[26]This could be contested in that both FCEV and BEV have higher energy efficiency than the fossil technology, as described in section 2. Still, by the lack of good, comparable data, this is assumed equal.

[27]Potential taxes for maintenance and insurance are disregarded.

[28]Le Duigou and Smatti (2014) state this cost as part of a TCO period of ten years, so this cost is divided by ten, and transferred to NOK.

[29]The annuity factor is given by: $AF = \frac{(1+r)^{Lifetime}r}{(1+r)^{Lifetime}-1}$

Table 3: Cost estimates for different vehicle types

	Fossil	FCEV	BEV	Unit
Investment cost (ex. tax)	104 270	239 598	139 026	NOK
Lifetime	15	15	15	Years
Discount rate	0.05	0.05	0.05	
Operating etc., cost per year	47 748	95 609	48 174	NOK
Annuity factor [29]	0.10	0.10	0.10	
Levelized capital cost	10 046	23 083	13 394	NOK
Total cost	162 063	358 291	200 594	NOK
Share of fossil	100	221	124	%

The starting point is that BEVs (battery technology) and FCEVs (hydrogen technology) have a higher purchase price than ICEs. The average price is based on an ICE are based on Reynaert (2014), where he uses a sample of bestselling vehicles in EU, and finds an average price of 22 250€for an ICE for these vehicles. According to EEA (2016*a*), the average price for a BEV in Europe is 30 000€, while for the FCEV there are few commercially alternatives today. This is thus based on the Honda Clarity and Nissan Mirai, and the price will then be around 51 290€[30]. The average valued-added tax (VAT) for vehicles in the EU is 21.4%[31] (ACEA, 2017*a*). Following that the VAT on average covers 42.18%[32] of all tax on motor vehicles in the EU, then 50.7% of the purchase price is tax-based. In other words, the investment cost for an ICE vehicle without taxes, will be 11 093€, or 104 270 NOK as shown in Table 3. Following Reynaert (2014), the VAT are mostly the same for BEVs and ICEs, and is in the range of 20-27%. Unfortunately, in

[30] About $60000 (Digital Trends, 2016; Car and Driver, 2017) with an exchange rate of 0.85.

[31] This the average for EU members, based on Table 1.1 in ACEA (2017*a*) and thus needs to be excluded from the investment cost, because of the planner argument stated above so that one needs the true costs for using an approach with alternative cost when considering how much to consume of different goods. This tax does not depend on the purchase price for all countries, for some it depends on e.g. engine power. However, this is disregarded, so that the VAT here is treated as a share of the purchase price of the vehicles.

[32] Based on the eleven countries from Table 1.4 in ACEA (2017*a*) that reports VAT numbers

part due to the large differences inside the EU on different tax exemptions and subsidies directed toward BEVs (and FCEVs), there is a difficulty with getting a good estimate on how much of the purchase price for BEVs and FCEVs in the EU that is tax based. Therefore, the same tax rate as for the ICE vehicles (50.7%) is withdrawn from the price of BEVs and FCEVs. This could mean that the price differential between conventional vehicles on one hand, and BEVS and FCEVs on the other, are larger than what is stated here, as the taxes and subsidies favors the clean alternatives to make the difference in price lower than what the real costs of production would reflect. In sum, the investment cost for FCEVs will be 239 598 NOK[33], and 139 026 NOK for a BEV. The lifetime of the different transport technologies is further thought to be equal. As noted in section 2, both FCEVs and BEVs have a challenge with durability with respect to the batteries, but this is disregarded in the estimates. The discount rate is set to 5%, the same rate used by Le Duigou and Smatti (2014) when they calculated the TCO for different vehicles. The annuity factor follows the assumed lifetime and discount rate, and the levelized capital cost is the investment cost (ex. tax) times the annuity factor. The conclusion from Table 3 is this that a BEV is not that much more expensive than an ICE vehicle, while a FCEV is still more than twice as expensive, given the assumptions stated. This seem like a fairly reasonable result.

5.3 Baseline scenario

In this section the baseline scenario is presented, followed by three different scenarios where some of the parameters are altered, before a plot of a possible subsidy to the clean technologies, based on the shadow values of experience, will be presented. This will include changing the substitution parameter between both transportation and non-transportation goods, and also between fossil and hydrogen on one side, vs. battery on the other. Finally, the learning rate for hydrogen technology will be changed.

[33] $60 000 minus the 50.7%, with an exchange rate of 8.1.

5.3.1 Parameter values

Table 4 shows the parameter values used for calculating the baseline scenario.

Table 4: Parameter values

Parameter	Value	Definition
θ	0.20	Share of transport in utility function
ρ	-1	Substitution parameter between transport and non-transport
η	0.50	Substitution parameter between fossil/hydrogen and battery
r	0.015	Discount rate
β	0.08	Discount factor for a five-year period, $(1+r)^5-1$
α_h	0.32	Learning parameter for hydrogen
α_b	0.13	Learning parameter for battery

The parameter values of ρ and η corresponds to an elasticity of substitution of 0.5 and 2 respectively. The former value is the same as Kverndokk and Rosendahl (2007) uses between electricity and non-electricity consumption and implies that the two types are considered complements. The value chosen further means that the relationship is relatively inelastic. This seems as a fairly reasonable assumption as the expenditure on transport, as a share of household's income, has been stable over time (Eurostat, 2017*a*) even though there have been relatively large fluctuations in fuel price. The latter value of 2 reflects that fossil and hydrogen technologies are substitutes to the battery technologies, which seem intuitive. The absolute value of this elasticity is however uncertain, so there will be presented below a scenario where this value is altered. The discount rate is set to 1.5% resulting in a discount factor of 0.08 over a five-year period. Finally, the learning parameters for the two technologies are in the baseline scenario set to 0.32 for the FCEV case, implying a learning rate of 20%, while for battery, the value 0.13 which is equivalent to a learning rate of 9%, and thus a progress rate of 91%. As found in the literature review from section 3, this rates are also uncertain, but the chosen value for the hydrogen is in line with Schoots et al. (2010) introduced above, where the learning rate was $21 \pm 4\%$[34]. As seen from Table 1, where the average learning rate reported was 17%, using a 20% rate in our baseline scenario is a somewhat optimistic approach. So, simulations where these

[34] This is, as explained in section 3 based on cost for the fuel cell, and not the hydrogen production in total.

rates are following a more conservative line will also be presented. The 9% learning rate for battery on the other hand, is based on an optimistic reading of Nykvist and Nilsson (2015)'s estimation of a learning rate between 6% and 9%.

5.3.2 Initial values

In Table 5, the initial values that is used is presented. These values, in addition to the parameter values in Table 4, is thus the input used for solving the maximization problem with the Excel Solver add-inn.

Table 5: Initial values

Term	Value	Definition
$\overline{M}$	100	GDP
γ	0.035	GDP growth per five years
τ	0.012	Carbon tax on fossil
ϕ	0.09	Increase in carbon tax per five years
$\bar{p}_f$	0.1	The constant cost of fossil
$\bar{\omega}_h$	0.1	Cost floor of hydrogen
$\bar{\omega}_b$	0.1	Cost floor of battery
ω_{h_o}	0.221	Initial cost of hydrogen
ω_{b_o}	0.124	Initial cost of battery
H_0	0.1	Initial experience for hydrogen
B_0	0.5	Initial experience for battery

The GDP in the EU is here taking a hypothetical value of 100, as shown in Table 5. The GDP growth of 3.5% over a five-year period, is equivalent to a 0.7% increase per year, which is the average for the EU as a whole over the period 2006-2014 (Eurostat, 2017*b*). As stated above, only the fossil technology is subject to a carbon tax. This tax is based on an estimate of \$100/tCO_2 from IPCC (2014), which implies 0.8 NOK/kg CO_2[35]. According to the IPCC (2015), the literature on mitigation scenarios operates with shadow prices for CO_2 both below \$50/tCO_2 in 2020 and also above \$100/tCO_2. Moreover, these "shadow prices exhibit a strongly increasing trend thereafter" (IPCC, 2015, p. 1149). And as it follows from the estimates on yearly mileage (13 000km) and

[35]With an exchange rate of 8.1.

liter per kilometer (0.75), there will be consumed 9 750 liter per year, releasing a total of 24 375 kg CO_2, when using an assumption that one liter of diesel and petrol (on average) releases 2.5kg of CO_2 (Ecoscore, 2017)[36]. This in turn, gives a total tax of 19 500 NOK per year. This implies a share of 12.0% of the total cost for fossil technology per year, and will thus be added to the original price of fossil technology. The tax is assumed to increase with 9% per five years, i.e. an annual increase of about 1.5%[37]. This estimate, and many others, will be discussed in the next section.

The constant cost of fossil fuel is assumed to have an hypothetical value of 0.1[38] which is also set as a cost floor for the two learning technologies, so that it is assumed that the cost of these technologies cannot be lower than for the constant cost of fossil technology. This is also uncertain, The Coalition Study (2009) for instance, report lower cost floor for battery technology than for the fuel cell case, while others, like Tsuchiya and Kobayashi (2004), find a cost floor that is even lower for fuel cells than what is found by The Coalition Study (2009). So, stating the same cost floor is of course a simplification, but it can be argued for.

The initial costs of hydrogen and battery technologies are based on the result in Table 2, namely that these costs are respectively 221% and 124% of the assumed fossil cost of 0.1. The initial experience is also uncertain, but it is assumed that there is five times as much experience in the battery technology versus the hydrogen technology as more BEVs are produced today compared to FCEVs.[39]

Figure 1 shows the result of the maximization problem from using the Excel Solver add-in, when the values stated in Table 4 and 5 is used, and the variables to be solved for are x_{ft}, x_{ht}, and x_{bt}. The other simulations below (Figure 2-4), uses the baseline values and parameters before one of these are altered.

In this scenario, we see that hydrogen will be utilized, but not reach 1% share of total transport before 2047. Further, we see that no fossil technology is being used after

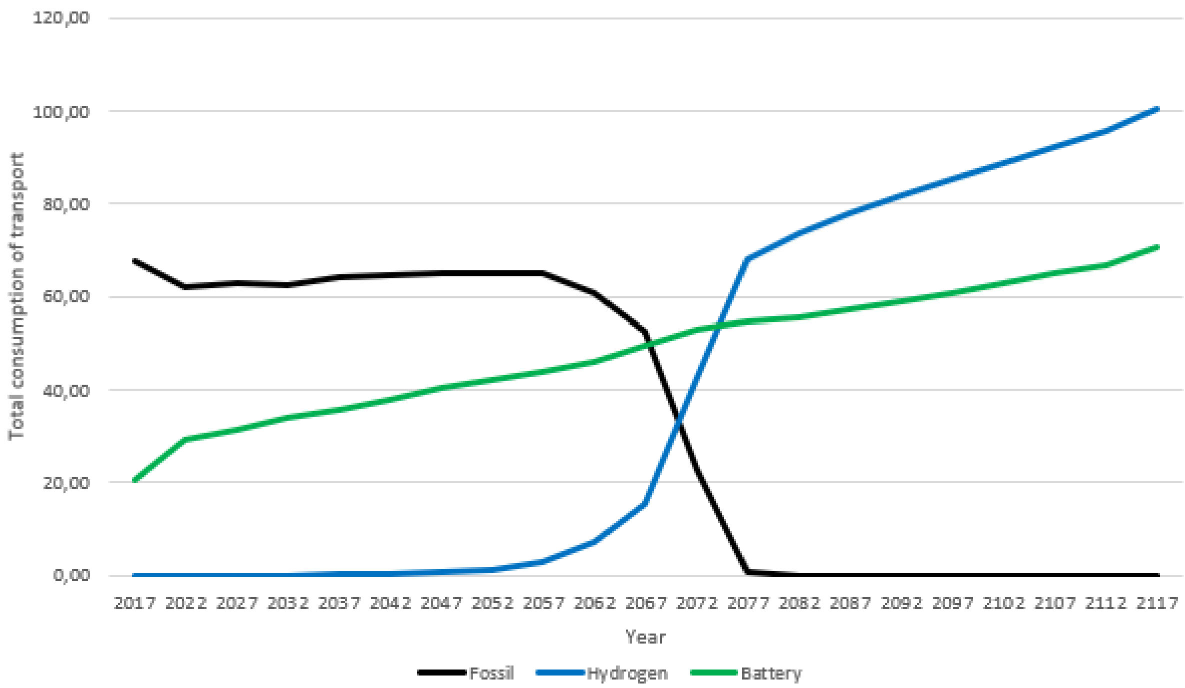
[36]It should be noted that these numbers will vary significantly between different models, and also if it is a new or old vehicle.

[37]The annual 1.5% tax increase will lead to a 71% increase in the simulations below during the next century

[38]Compared to the total GDP of 100, this is thus a high value.

[39]From the simulations, the total consumed transport in 2017 is about 80-100 in total for several different simulations, so the initial experience value for battery corresponds to about 0.5% of consumed transport in 2017, and about 0.1% is then hydrogen. In other words, this fits OK with today's situation.

Figure 1: Baseline scenario



2077, which reflects that the prices for hydrogen have become lower than for the fossil alternative. Since these technologies are considered perfect substitutes, then no fossil will be used after 2077 as this price is getting higher and higher due to the carbon tax. For hydrogen, it will become lower over time due to the increased experience. The result that hydrogen will be used in a small scale from 2047, means that even though the price then is higher than for fossil (remembering the perfect substitute assumption), it will be optimal to start investing and thus consume transport from the hydrogen technology. This is because it eventually will reach a lower price than for the fossil (including the carbon tax) due to the learning and experience effects. Further, the model suggests a battery share of 23% already in 2017, implying that today's level of BEVs is be too low. Figure 1 also indicates that there will be a fairly high level of battery technology in all periods. This means that the substitution elasticity between the two (fossil/hydrogen and battery) are relatively low, which is also reflected by the 2.0 value in elasticity. This could for instance be the case if BEVs were highlighted by the authorities to be 'the best' transport alternative from an environmental point of view (disregarding the FCEV alternative). Thus, many would be convinced to buy BEVs, even though the more unfamiliar FCEVs could be a better alternative. If this low elasticity was not the case, i.e. that there was a higher substitution elasticity, the cheapest alternative amongst the three would probably have a higher share of total transport. This will be investigated in Figure 3 below.

Further, as illustrated in Figure 1, fossil technology is the cheapest technology available for quite some time, including the emission tax. As hydrogen starts to be introduced, it quickly 'takes over' as it becomes the cheapest technology. This is due to the fact that the learning rate is assumed higher for this technology than for the battery case. The rate of this transition from fossil to hydrogen will be discussed below.

Another aspect that cannot be read from Figure 1, is that the share of the budget that is used on transport, is 13% of the GDP in 2017 (and varies between 11 and 13% throughout the time horizon).[40]

5.3.3 Changing the substitution parameter between transport and non-transport

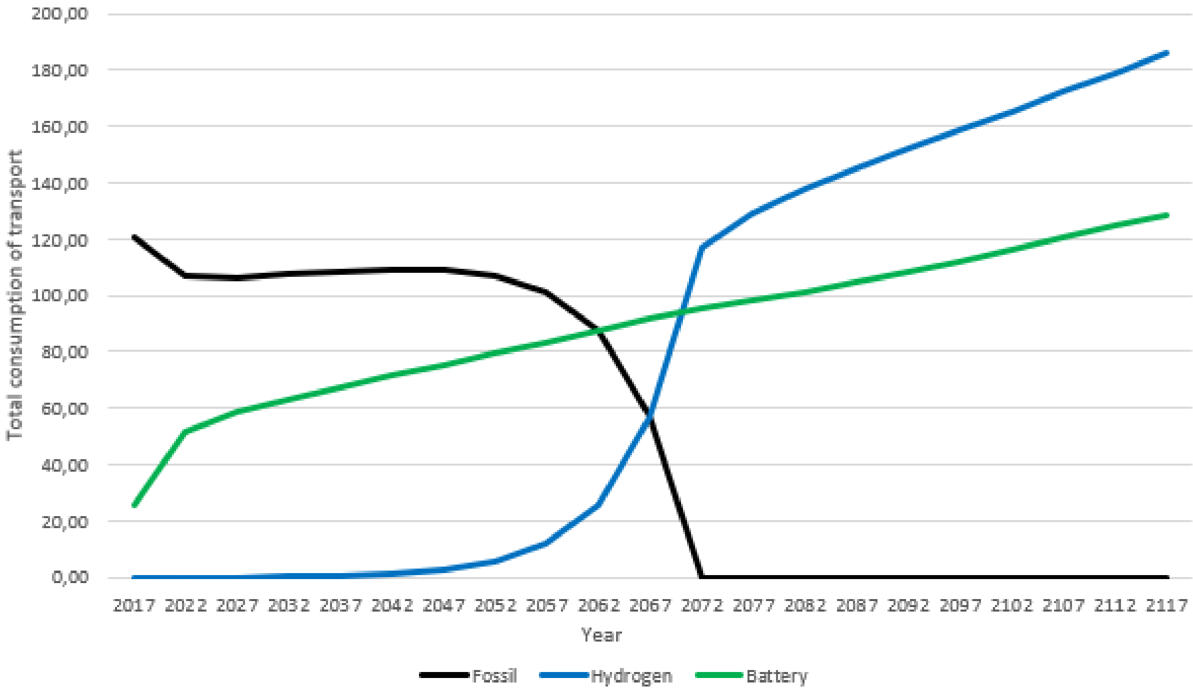
Now the substitution elasticity between transport and non-transport consumption is changed from 0.5 to a substitution elasticity of 0.99 to make it less clear complements. As we know that an elasticity below 1 indicates complements while larger than 1 means substitutes, transport and other consumption are still seen as complements. The result is presented in Figure 2.

Figure 2 that the results *between* the three technologies are not altered significantly from the baseline scenario in Figure 1. One change is that now hydrogen is being introduced a bit earlier. It reaches 1% share of total transport in 2042, compared to the baseline scenario. This also follows from the fact the fossil is phased out earlier: from 2072 no fossil technology will be consumed, compared to 2077 in the baseline scenario. As is also evident from Figure 2, the total consumption of transport is increased from the baseline scenario.[41] This means that compared to the old elasticity, the new elasticity means that the planner now values transport higher relatively to non-transport consumption, compared to before. The other way around is also tested, i.e. to an elasticity of 0.01, and got the same relationship between the technologies, but now with a lower share of

[40]This is a bit higher than in reality, which was about 7% in 2015, including other types than just road transport (Eurostat, 2017*a*). However, given that the GDP is taking a hypothetical value, this does not seem too bad.

[41]As can be seen from the numbering on the y-axis.

Figure 2: Changing elasticity between transport and non-transport



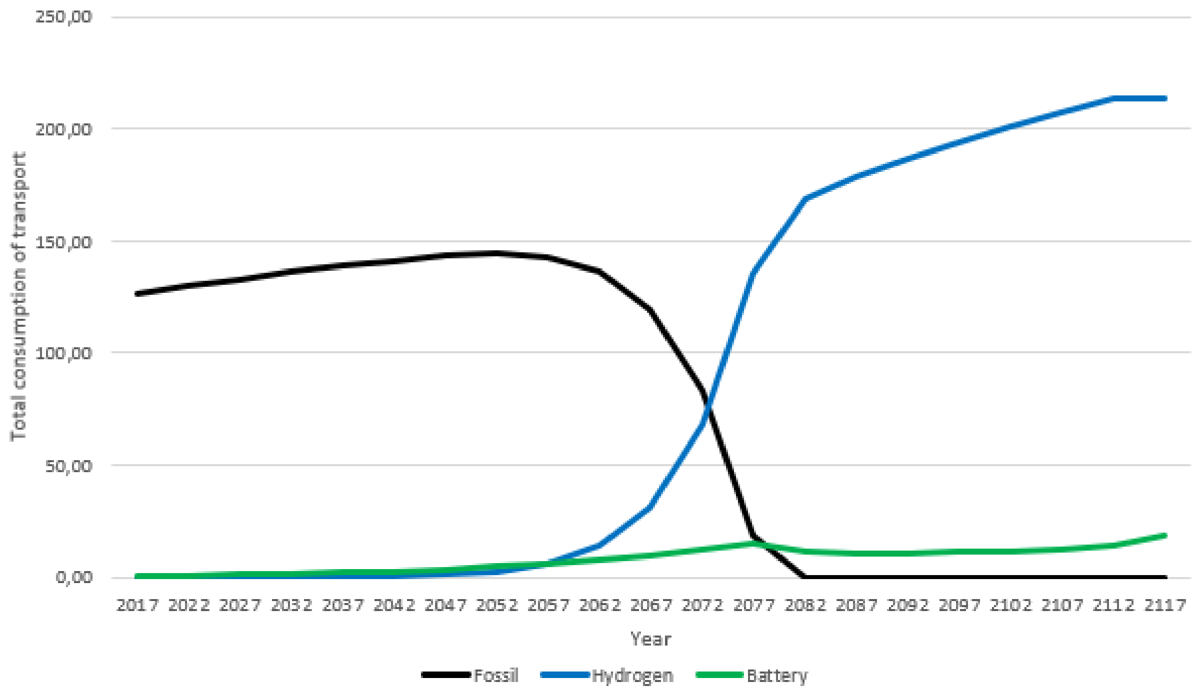
GDP used on transport than for the baseline scenario. The time profile of the hydrogen introduction was still similar to the that scenario. And as the main focus is the three technologies in relation to each other, these results are not affected much when altering the elasticity between transport and non-transport consumption.

5.3.4 Changing the substitution elasticity between fossil-hydro and battery

As highlighted in the baseline scenario above, the substitution elasticity of 2 gives a relative high share of the battery technology in transport consumption throughout all periods. In other words, there is a demand for this technology even though there is a cheaper alternative available, namely fossil in the first periods, and hydrogen in the latter period. But here hydrogen and fossil are made more of a clear substitute to battery, by increasing the substitution elasticity from 2 to 10. This means that the price difference between them is a bigger determinant for the outcome reached than is the case in the baseline scenario.

Figure 3 shows that now almost no battery technology will be consumed from the start and throughout the time horizon, as fossil is a cheaper alternative in the beginning,

Figure 3: Changing elasticity between fossil/hydrogen and battery technology



and that hydrogen becomes a cheaper alternative than battery almost immediately after it is introduced. This is because of the lack of experience for the battery technology. Even so, as fossil/hydrogen and battery are not perfect substitutes, some battery will be consumed.[42] In other words, it is still optimal to use all three technologies in this scenario, though with very a low share for the battery technology as it never becomes is the cheapest alternative of the three technologies.[43]

Another result in Figure 3, is that now the hydrogen is being introduced at a bit higher rate than in the baseline scenario (though not a very big difference). This can reflect the fact that now battery does not work as a 'buffer' in the transition from fossil to hydrogen as it does in the baseline scenario. The relationship between transport and non-transport is relatively inelastic, as stated above, more or less the same amount of transport in total will be demanded in each period, but now very little of this total demand will be for battery, which could imply a quicker phasing in of hydrogen.

[42] If the same simulation is done with an elasticity of ~ 1, then no battery will be consumed at all.

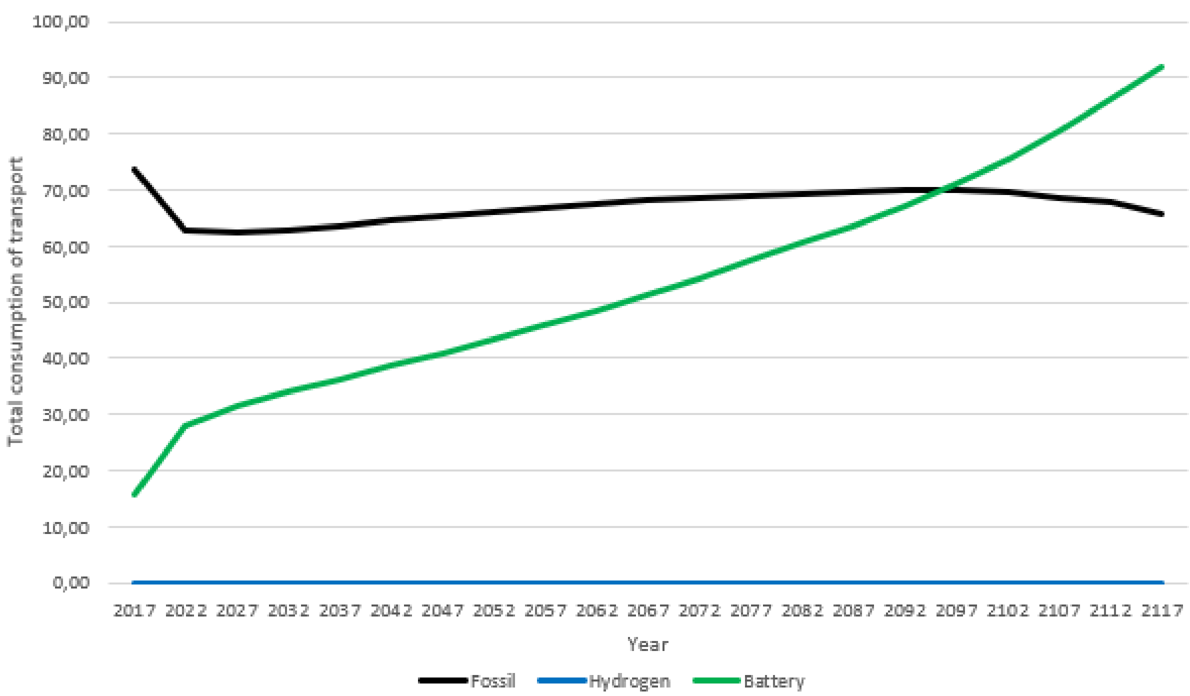
[43] The simulation was also done with an elasticity of 5, which made the battery technology to be used with a similar slope as in the baseline scenario, but with a lower share of total transport throughout the horizon.

Further, the use of fossil in the early periods are higher than in Figure 1, which reflects that in the beginning of the time horizon now almost only fossil is used. And since this technology is from the outset the cheapest one, there is more left of the budget as none of the more expensive technologies is included from the beginning.

5.3.5 Changing the learning rate

As the learning rate for hydrogen is assumed to be in the upper echelon of what the literature states, the following scenario will now take as an outset that hydrogen and battery technology has an equal learning rate of 13%. This is a more conservative, and perhaps, more realistic approach than in the other scenarios. From Table 1 above, the learning rates reported for fuel cells, was mainly about ±15%, which makes 13% seem like a reasonable estimate.

Figure 4: Changing the learning rate for hydrogen from 20% to 13%

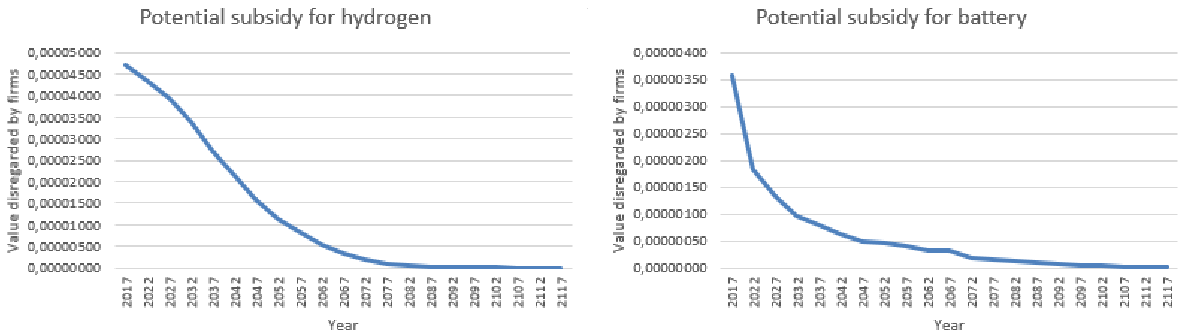


The result presented in Figure 4 shows a scenario where zero hydrogen is used throughout all the periods. In all the other scenarios, the hydrogen technology has surpassed battery in cost, due to the fact that it is assumed to have a higher learning rate than for the battery technology. Now, as we know from the assumptions above, that the initial costs of hydrogen are higher than for battery, and with an equal learning rate, so hydrogen will here never catch up with the battery price. Still, we know from the elasticity between fossil/hydrogen and battery, that we will use at least two technologies at once, one of them being battery. The result in Figure 4 indicates that as the cost of hydrogen is reduced at a slower rate, it is no longer optimal to produce and consume any transport with this technology, as the future benefit of this cost reduction now is smaller than the scenarios above. This highlights the importance of the learning rate in the model, as it is the driver of the cost reductions.

5.4 Potential subsidy to the clean technologies

It is likely that, without a social planner in place, it would be invested too little compared to what is optimal if there were a free market solution. According the arguments presented above in section 4.1, like firms not internalizing the full effect of the gained experience, there could be justification for EU-institutions to subsidize the technologies. The marginal value of experience for the two technologies could thus be used as a reference for a possible subsidy towards the producers. By this, it is here meant the whole term where λ_h and λ_b is included in the FOCs for hydrogen and battery from (19) and (20).[44] Figure 5 gives an illustration of the development of these values.[45] The value plotted reflects thus the total utility gain of increasing experience.

Figure 5: Potential subsidy to the clean technologies



[44]The value of the shadow values isolated, i.e. λ_h and λ_b are plotted in the appendix (Figure 6).

[45]It should be noted that this serves an illustrative purpose as the equations are based on a continuous time approach, and the values are from solving a problem in discrete time. Still, there is nothing intrinsically wrong with this approach.

Figure 5 states that the utility value of experience are higher for both battery and hydrogen experience in the early phases of the horizon, before it falls significantly. We further see that the shadow price is somewhat higher in 2017 for hydrogen experience than for battery. This could reflect that the learning potential is higher for hydrogen, both because the learning rate is assumed higher, but also that in 2017 it is assumed that the accumulated production, thus experience, are higher for battery than for hydrogen. The latter argument reflects a feature of the learning rates: as it show a relationship exponentially, the cost reduction will be larger if there is little accumulated production (intuitively it requires relatively less to double the production if there are little initial production), while further increase in experience will yield a lower 'payoff'. In addition, the decline is smoother for hydrogen than for battery. This is due to the fact that hydrogen is being used at a very low scale in the beginning, but increasingly throughout the horizon, while for battery, the production increases drastically already in the first period from 2017 to 2022. Further, Figure 5 states that as time goes by, the subsidy toward the clean technologies would move to zero. This could mean that the cost for hydrogen and battery technology in the end of the horizon either is getting close to the cost floor, or that increasing the production marginally does not affect the costs as much when the production have reached a certain level, or perhaps both. This is intuitive as the value of an additional unit of experience after there have been mass production, does not affect the total cost in a significant way as it would have in an initial phase.

The absolute numbers of the shadow values are difficult to give a clear interpretation of. Relative to the cost (and price) of the cheapest technology in 2017, namely fossil, is 0.1 (as stated in Table 5), the shadow values are small (less than 1% of the fossil price in 2017). This could possibly be due to the GDP which is set to 100. This makes the transport market very small.[46] As the values reported here are likely to depend on the share of the market, the bigger the market, the bigger the value of a decline in costs. In addition, as the values in the estimates are not absolute values from the real world, it is, again, the *relationship* that is the most interesting to interpret. In that respect, Figure 5 seems to represent a reasonable result based on what one could expect.

[46] As the share of total GDP used on transportation is 11-13% throughout the time horizon.

6 Discussion

In the following section, challenges with the model and scenarios presented will be discussed. This section will discuss the approach used and the different scenarios presented, in addition to the realism in the results presented. This includes how the parameter values could change the results if altered. Finally, questionable estimates will be highlighted.

6.1 The social planner approach

As the problem is solved by a social planner, it is essential to have in mind how realistic these scenarios are to implement in practice. The main problem will be to make the agents in the market for transport internalize the experience effect. If an assumption that there are some spillovers between the different producers, increasing experience for one producer will also lower the cost for other producers. As there are lots of producers for both batteries and fuel cells today, there is a possibility of them not taking the last term on the left-hand side in equation (21) and (22), i.e. the term where learning is included, into account. If the firms were not myopic, they would of course internalize some of the learning, namely their own internal learning effect that reduces their own future cost. But since one producer only takes its own situation into account when it decides how much to produce, then the positive effect of reduced costs for other producers in the industry, will be neglected. This could possibly pave the way for a subsidy directed to one (or both) of the learning technologies, as also discussed above.

The subsidy approach is not straightforward. As there are several technologies present when deciding which technology to subsidize, there will be a chance of 'picking the wrong winner', i.e. subsidizing the 'wrong' technology. This is a problem if there exists a possibility of *lock-in*. Liebowitz and Margolis (1999) states that lock-in, as it is understood in the literature, is a situation where there is lock-in to something bad, based on previous events. The result is in an inferior economic outcome, while there exists known, superior alternatives. If the governmental support directed to BEVs (as in many EU member states today ACEA, 2017*b*), leads to the FCEVs not diffusing into the market, this would be a lock-in if it welfare superior to have a future *with* FCEVs.

6.2 Scenarios

In the baseline scenario, hydrogen starts out with a low production, before reaching a higher rate when consumption of fossil technology is starting to decline around 2060. As this is the optimal path, given the assumptions and estimates, there seems to be no clear challenges when introducing the hydrogen technology. Here, the assumption about perfect substitutability between fossil and hydrogen technology, plays a key role. An implication of this assumption in the model, is that producers of hydrogen technology will hesitate to enter the market, as it has a much higher cost than fossil today, even including the carbon tax on fossil fuel, and the only reason for a consumer's choice is price. Since this cost only will start to decline when someone takes the lead and start to produce even with high costs, the incentives for hydrogen producers to start producing are limited. Even though it could be optimal to produce more hydrogen in the future, the situation with a lower cost fossil technology today, could hinder the hydrogen producers to invest in this technology. This could for example be if the firms have limited capital resources that makes the cost in the early stages so high that it will not enter the market before the cost have been reduced. It thus need another producer to make the 'first move', in order to make the cost manageable. If this is true for all hydrogen producers, then of course no one would start to produce, as all are waiting for others to bear the high cost burden in the early phases.

Another striking fact in the baseline scenario, is the high growth rate of the hydrogen technology when it is first introduced. It is difficult to say something about how realistic this quick 'phasing in' of the hydrogen technology is. As the learning rate is uncertain, as will be further discussed below, the rapid cost decline following this rate is also uncertain. The infrastructure needed to be developed for such a deployment of hydrogen makes the fast transition even more questionable. Since the infrastructure needed is assumed to be in place, all the scenarios where hydrogen and/or battery is used, could thus be too optimistic. In The Coalition Study (2009), the infrastructure cost for hydrogen represents only 5% of the overall TCO, as mentioned above, which can be argued is not that big a share. Others again see this as a major issue for making FCEVs a commercially viable alternative. Nevertheless, if the introduction of the hydrogen technology happens too fast in the model compared to what is considered more realistic, then maybe hydrogen should be introduced at an earlier stage, so that it has 'more time' to reduce the future costs to become competitive.

In addition, there could be other challenges that makes such a rapid increase less likely. This could be due to consumer preferences, as Egbue and Long (2012) pointed out. Consumers tend to be relatively reserved when introduced to new alternatives if they consider the existing alternative a good one, as is likely to assume when it comes to the well-known ICE vehicle. On the other hand, environmental awareness has increased in later years. This could point in the other direction, in that consumers will be more likely to choose an environmental alternative even if the price could be somewhat higher than for a 'dirty' one.

6.3 Constant elasticity of substitution

The assumption of constant elasticity of substitution does probably not hold in reality. As the technologies develop, and consumer preferences may change, there is reason to believe that the elasticity would change over time. As the elasticity between fossil and hydrogen on one side, and battery on the other, is set relatively low in the baseline scenario, the elasticity could possibly increase throughout the horizon. It could possibly be that there is a low substitution today because of the advantage battery cars may have in e.g. cities, compared to the fossil technology. But, as hydrogen gets cheaper and maybe catches up with battery costs, and both types have been accepted as a viable alternative by the consumers they could see them as clearer substitutes[47], e.g. with a substitution elasticity of 10, as tested in figure 3. In that figure, the battery technology is almost not used at all and the cost will never be significantly reduced, while in the baseline scenario with an elasticity of 2, battery is suggested to a 23% share of total transport in 2017. I.e. with a reduced cost already in the first period. How these two scenarios would be if they were 'grouped' together (for instance by starting with an elasticity of 2 in 2017, before reaching 10 in 2117), would be an good subject for further analysis. This is however not possible as there is assumed constant elasticity of substitution in this thesis.

[47]This questions somewhat the assumption of perfect substitutability between ICE vehicles and FCEVs. With respect to local air pollution and noise pollution, maybe FCEV and BEVs could be seen as more perfect substitutes than that between an ICE car and a BEV.

6.4 Challenges when using learning rates

Predicting future scenarios is a difficult task. In the model, the learning rates plays a major role in what scenario is predicted. As stated in section 3.1 above, there are several mechanisms at work when considering learning or experience curves, some of which are even debated if it should be considered a learning effect at all. The learning rates are thus subject to a number of challenges, some of which will be elaborated on in this section.

Following Anandarajah et al. (2013), there are several considerations that needs to be highlighted when working with learning curves. First, there is nothing in a technology *itself* that gives it a particular learning rate, and the use of historical learning rates does not necessarily give a good indication of the future development of these rates. The rates based on history are subject to different processes, like the learning and experience that is the focus in this thesis, but also regulatory changes, developments in the supply-chain and so on (Anandarajah et al., 2013). In other words, to isolate the learning effect is hard in itself, and becomes even more so when taking into consideration that the cost development of a technology is influenced by a number of processes that differ over time and place. A second challenge with learning rates, is that the rates differs more often than not throughout the life-cycle of a technology (ibid.). In the model presented above, it is for instance assumed a learning rate for the hydrogen technology that is the same in 2017 as it is in 2117. Often, the rates are higher in the initial phase of a new technology being established, when there intuitively are much that can be learned, but as time goes by and the technology matures, it becomes harder to find new ways to lower the cost. Nevertheless, as highlighted by Anandarajah et al. (2013), in bottom-up models like the one presented here, it is not customary in "bottom-up energy systems modeling of learning rates [to use differentiated learning rates]" (Anandarajah et al., 2013, p. 3425).

Another approach when using learning curves, for getting closer to an isolated learning effect, is to use a two-factor approach instead of the standard one factor approach, where only cumulated production is measured. An example of this was presented above, by Mayer et al. (2012), where they tried to differentiate between cost reductions due to the cumulative production on one side, and R&D on the other. This could also have been taken as an approach in this thesis. However, it is seldom that technologies are fostered *only* through R&D, or *only* through the use of the technology without any kind of R&D. According to Anandarajah et al. (2013), it is possible that the use of a "single learning curve may actually be better placed to represent these effects" (Anandarajah et al., 2013, 3425). This view is supported by Watanabe et al. (2000), where it is stated that learning by doing and learning by researching mechanisms reinforces itself. The approach to use a wide definition of learning, or experience, as used in this thesis, may in other words be a good approach.

Kahouli-Brahmi (2008) also acknowledge the R&D related problems to the learning rates, in addition to discuss the possibility of omitted variable bias, which is a problem since there of course are other variables than just the accumulated production that influences the cost. Söderholm and Sundqvist (2007) note for example input prices and scale effects as the most obvious examples of variables that clearly will affect the cost. The problem with scale effects is already touched upon, and since the model does not explicitly deals with the distinction, and treat scale effects as a pure learning or experience effect, it is likely that the learning effect could be overestimated. This will alter the results in the simulation, especially when we know that if the learning rate for hydrogen is reduced sufficiently, the total consumption of this technology could be zero.

Another obvious problem with learning and experience rate, is how to best *operationalize* the concepts. As the negative relationship between accumulated output and cost is widely established, there is need to investigate whether this measure actually capture the specific impact of the learning, and not just general technological progress (Söderholm and Sundqvist, 2007).

In sum, the learning rates has several problematic features. One is to find an actual rate that is as close to reality as possible. Another is how much of the rate that actually are due to *learning*. To cite Köhler et al. (2006), "the strongest reason for applying them [learning rates] in long-run modeling is not that these issues have been resolved, but rather that the evidence for *some* degree of experience-based cost reduction is overwhelming" (Köhler et al., 2006, p. 34). Learning is an inherently somewhat diffuse concept, which is one reason why the total accumulated output is used as a proxy for the learning progress. Therefore, as this thesis uses this approach, it is necessary to have in mind the problematic aspects of these curves, and not state any result with absolute certainty, rather highlight the findings as a possible future scenario given the methods and values used, and at the same time being aware of the limitations of the approach.

This in turn leads to another troublesome aspect with the scenarios above, namely the initial values and parameters that are used in the simulation above.

6.5 Uncertainty about values and estimates

As the simulations above to some degree serves an illustrative purpose, the scenarios should not be interpreted as a true projection of the future, but mainly how the model works, like for example what it takes for hydrogen to be introduced.

To begin with, the ideal cost inputs in the model would be actual values in absolute numbers, and not a transformation based on the relationship between the different technologies. Then it could more realistically be found out something about the transport consumption in relation to total consumption. This is now hard to state with certainty, for instance by the fact that there is used an hypothetical value of the GDP. As the focus is on the three technologies relationship in between, the results found will hopefully not be altered in a significant direction if there were used 'real' numbers, but the total picture is of course not a good representation about the development and the economy as a whole. If using absolute numbers, it would maybe also be easier to calibrate the model to todays situation. One could for example find the total demand for road transport in the EU, and try to calibrate the model to this for a realistic initial phase of the model. In other words, the model would give a more realistic (total) scenario if the TCO calculated for the different technologies were used directly in absolute numbers, in addition to an absolute number of the GDP.[48]

The TCO itself is also uncertain. As the difference in investment cost, is very large *inside* the different groups, to base the TCO of an *average* of this, is not very precise. This is also true for the taxes deducted for the different vehicle types. Further, it is complicated to find an average lifetime expectancy of the different vehicles. Some points to low durability for batteries and fuel cells as a potential problem, but as it is also considered that these vehicles have lower maintenance costs, this again could imply that the vehicles themselves have a higher lifetime. Another complicating factor is that a large majority of the FCEVs and BEVs are relatively new vehicles, which makes it even harder to state with of a certainty the lifetime of these vehicles.

[48]This is not done because, despite several different attempts, the Excel Solver add-in used for the utility maximization resulted in numerous error messages when total GDP numbers for the whole of the EU were the inputs.

Further, the operating cost of the different types are also subject to uncertainty. The fuel prices (i.e. petrol/diesel prices, hydrogen prices, and electricity) are first of all hard to find a good measure for as the prices of fossil fuels varies quite a bit, as well as the cost for fuel cells and batteries are in constant development. It would probably better to find up to date numbers of the different fuel costs, and use them in absolute value separately instead of basing the fuel differences on Le Duigou and Smatti (2014), but this is still one of the few papers found, that actually compares this explicitly. Nevertheless, predicting future fossil fuel prices will never be straightforward.

The discount rate used in the TCO calculation is also debatable, but as both Le Duigou and Smatti (2014) and Kverndokk and Rosendahl (2007)[49] also uses a discount rate of 5% for investments, could imply that this choice seem like a viable alternative. The argument to find use new, updated numbers instead of following Le Duigou and Smatti (2014), is also true for the maintenance and insurance costs. It would of course be optimal to find new and updated estimates. The discount rate in used in the utility function is also uncertain, and has been highly debated (see for instance Stern, 2007 and Nordhaus, 2007). If the model used a higher discount rate, it would value the future cost reduction for hydrogen and battery less, and the optimal path would probably be to use more of the dirty technology and less of the clean technologies. A lower discount rate on the other hand, would give an opposite result.

Another important aspect for the results presented, are the carbon tax placed on the fossil fuel technology. As the cost for the fossil technology is assumed constant, the only driver behind this technology's cost increase, is the tax. Further, following the fact that there is a cost floor on the two clean technologies subject to learning, in the long run (if both of these are produced on a sufficiently large scale) the cost would reach this floor, which makes the carbon tax the only thing that makes the costs between the technologies differ. The tax on emissions is based on an estimate from IPCC (2014), which is also uncertain, but still probably one of the more thorough estimates. The growth rate set at 1.5% and results in the price for fossil fuel to increase from 0.10 in 2017 to 0.17 in 2117, i.e. a 70% increase. The statement by the IPCC that the original shadow value set on emissions will increase rapidly in the future, is however not precise, so that the estimate of 1.5% is highly uncertain. Nordhaus (2014) found a social cost of carbon of "only" $

[49] This is however based on electricity investments, and not vehicles as Le Duigou and Smatti, 2014 do.

18.6/t CO_2, but on the other hand a growth rate of 3% per year to 2050. Compared to this, it could be that the starting tax is too high, but also that the growth rate is too low. The central point is that the carbon tax rate has a crucial role for the scenarios reached above, and that this is an uncertain estimate.

The conclusion to draw from this section is that the model optimally would have more realistic inputs, so that the scenarios drawn from it would be more plausible than the results presented here. This in turn also implies a challenge when investigating the different technologies studied in the literature: the existence of good, reliable, and comparable data. Also highlighted by Anandarajah et al. (2013), it should be noted that, as with all long-term modeling, the result is subject to considerable uncertainty, which makes the general patterns more interesting than specific outputs. The model describes well the relationship between the three transport technologies, and what *could* be possible future scenarios. It has been challenging to find reliable data to use in the model, which in turn could be a motivation for further research.

7 Possible extensions and further research

7.1 Decentralize decisions

A possible extension when originally stating the problem as a social planner approach, is to instead look at decentralized decisions from the agents in the market, which was touched upon in section 6.1. This would obviously make the results more realistic than the case that has been investigated in this thesis. If the different agents in the economy are considered to be myopic so that neither is taking the learning into account, then this would lead to too little investment in the technologies subject to learning.

To follow this approach further, one could model the demand for the different transport technologies, with one demand for fossil and hydrogen combined (as they still would be considered perfect substitutes) and another one for battery. Combining this with the supply of the different technologies, this approach would describe a static equilibrium for the different transport technologies at each point in time, when the government's (the EU-institutions) instruments are taxes and subsidies. The government (the EU) could choose which learning technology to subsidize, or perhaps both (at least according to some of the simulations above), to lower the supply curve of these technologies, and impose a tax on the fossil so as to raise this curve. The demand for fossil and hydrogen, would thus depend on the price of these technologies, where the consumers would choose the minimum price (included taxes and subsidies), but it would also depend on the price of batteries as they are substitutes. The same would be true for the demand for battery transport.

7.2 Include other types of electric vehicles

As this thesis only focuses on battery electric vehicles and fuel cell electric vehicles, a natural extension would be to include other electric vehicles as well. Especially hybrid and plug-in hybrid electric vehicles are often considered together with BEVs and FCEVs. As these types of electric vehicles uses both an electric motor and an internal combustion engine, they have the possibility to 'bridge' the transition from fossil fuel driven vehicles, to electric vehicles. As the model presented above gives indication of a relative fast phasing in of FCEVs, and to a certain degree BEVs (remembering that the model suggests a high share of these vehicles already today), this was discussed above as perhaps not too realistic. The use of PHEV and HEV could thus make the transition away from fossil fuel smoother, as part of the BEVs and FCEVs in the scenarios could be replaced by these hybrid types in the transition period toward full electrification.

7.3 Network effects

Not considered in this thesis, is the possibility of network effects, which is clearly relevant for both the battery and hydrogen technology. The essence of network effects lies in the phrase: "it can pay to follow the crowd" (Farrell and Klemperer, 2007, p. 43). For the battery technology in transport, the utility of a BEV will be dependent on the number of chargers, which in turn will be dependent on how many BEVs there already are on the roads. As more and more demand BEVs, the network for chargers are likely to increase, and thus the utility of buying and using the BEVs. This is formally known as an *indirect network effect*, as Katz and Shapiro (1985) define as a situation in which: "[T]he utility that a given user derives from a good [also] depends upon the number of other users who are in the same network" (Katz and Shapiro, 1985, p. 424), i.e. the size of the network. The same argument holds also for the hydrogen technology, as analyzed by Greaker and Heggedal (2010). They found that if the cost of establishing hydrogen filling stations were too high, or if the technology in itself was immature (i.e. basically the same as the outset for the model presented in section 4), then there will be only one equilibrium where only ICE cars[50] are present.

8 Conclusion

As a measure for reducing the large amount of GHG emissions from fossil fuel cars in the transport sector, many see battery electric vehicles as a possible solution. However, hydrogen cars have also a potential to play a crucial role if the emissions are to be reduced sufficiently to reach the targets set by the EU. This thesis has analyzed and compared the different technologies that lies behind these alternatives. This was done in a theoretical model, also combined with fossil technology. The two clean technologies are subject to learning, while the fossil technology needs to pay a tax on emissions.

The results from the theoretical model suggests that the learning effect may not be sufficiently internalized in a market solution. Hence that it will be produced too little relative to the optimal consumption path of the two clean technologies that are subjected learning. This could in turn call for a subsidy directed to these clean technologies, which will be in the magnitude of marginal utility gain from increased experience for these two technologies.

It was shown in the simulations for what it could take for hydrogen technology to diffuse significantly into the road transport market during the next century, which required a relatively high learning rate. The battery technology is by the model suggested to have a larger share of todays transport than what is the case. Further, even though fossil and hydrogen are assumed to be perfect substitutes, the baseline scenario suggest that it is optimal to introduce the high cost hydrogen technology, due to a potential for lower cost than fossil in the future. This reduction is thought to be caused by the learning taking place in production.

If the substitution elasticity between hydrogen and fossil on the one hand, and battery on the other, is altered so that they become clearer substitutes, then almost no battery technology will be used. This is due to the fact that as the alternatives are clearer substitutes, the cheapest option will increasingly be preferred.

The results from the simulations should be interpreted with caution. The model

[50] Greaker and Heggedal (2010) does not include BEVs in their analysis.

introduced is stylized and shows a simplified version of the reality. The estimates used are also subject to uncertainty. As learning is considered to be the main driver behind future cost reductions for hydrogen and battery technology, the values used for learning plays a key role for the results. With an optimistic learning rate, the hydrogen technology will reach a majority of transport consumption during the next century. When this rate is reduced to the same rate as for the battery technology, however, the optimal path will be not to use this technology at all.

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A Deriving of expressions

A.1 FOC for the hydrogen technology

Differentiating H^{CV} with respect to x_h gives:

$$\frac{dH}{dx_h} = \big[\theta T^\rho + (1-\theta)C^\rho\big]^{\frac{1-\rho}{\rho}} \big(\theta T^{\rho-1}\frac{dT}{dx_h} + (1-\theta)C^{\rho-1}\frac{dC}{dx_h}\big) + \lambda_h = 0 \tag{40}$$

by dividing the whole expression with the first part (the square brackets) and moving the $\frac{dC}{dx_h}$-term to the RHS:

$$\implies \theta T^{\rho-1}\frac{dT}{dx_h} + \frac{1}{\big(\theta T^\rho + (1-\theta)C^\rho\big)^{\frac{1-\rho}{\rho}}}\lambda_h = -(1-\theta)C^{\rho-1}\frac{dC}{dx_h} \tag{41}$$

which is equivalent to:

$$\implies \theta T^{\rho-1}\frac{dT}{dx_h} + \big(\theta T^\rho + (1-\theta)C^\rho\big)^{\frac{\rho}{1-\rho}}\lambda_h = -(1-\theta)C^{\rho-1}\frac{dC}{dx_h} \tag{19}$$

i.e. (19). The same procedure is done to calculate (20), i.e. the FOC for the battery technology.

A.2 Expressions for the shadow values

First, the expressions for λ_h and λ_b are derived in the following way, based on (19) and (20). To get λ_h on one hand, the term including $\frac{dT}{dx_h}$ are moved to the RHS, before dividing both sides by the term in front of λ_h. This results in:

$$\lambda_h = \frac{1}{\big(\theta T^\rho + (1-\theta)C^\rho\big)^{\frac{\rho}{1-\rho}}}\big(-(1-\theta)C^{\rho-1}\frac{dC}{dx_h} - \theta T^{\rho-1}\frac{dT}{dx_h}\big)$$

$$\implies \lambda_h = -\big(\theta T^\rho + (1-\theta)C^\rho\big)^{\frac{1-\rho}{\rho}}\big((1-\theta)C^{\rho-1}\frac{dC}{dx_h} + \theta T^{\rho-1}\frac{dT}{dx_h}\big) \tag{42}$$

If substituting in for $\frac{dC}{dx_h} = -p_h$, the expression is equivalent to the λ_h that is substituted into (27):

$$\lambda_h = \big(\theta T^\rho + (1-\theta)C^\rho\big)^{\frac{1-\rho}{\rho}}\big((1-\theta)C^{\rho-1}p_h - \theta T^{\rho-1}\frac{dT}{dx_h}\big) \tag{43}$$

The same procedure is done for the battery case.

A.3 The costate equations

The state variables of hydrogen, H_t, and battery, B_t, lies inside the budget constraint in the following way[51]:

$$C = \overline{M} - (p_f + t_f)x_f - (\bar{\omega}_h + \omega_h(0)H_t(t)^{-\alpha_h})x_h - (\bar{\omega}_b + \omega_b(0)B_t(t)^{-\alpha_b})x_b \tag{44}$$

This means that the state variables only appears once in the Hamiltonian, i.e. in the term with consumption. Differentiating this wrt. the state variable for hydrogen gives:

$$\frac{dC}{dH_t} = -(-\alpha_h)(\bar{\omega}_h + \omega_h(0)H_t(t)^{-\alpha_h-1})x_h$$

$$\implies \frac{dC}{dH_t} = \alpha_h \omega_{h_o} x_h H_t^{-(\alpha_h+1)} \tag{45}$$

which is the same as stated in 4.2 above. And since the Hamiltonian is $H = \Big[\theta T^\rho + (1-\theta)C^\rho\Big]^{\frac{1}{\rho}} + \lambda_h x_h + \lambda_b x_b$, then differentiating this wrt. H_t will be:

$$\frac{dH}{dC}\frac{dC}{dH_t} = \frac{1}{\rho}\Big(\theta T^\rho + (1-\theta)C^\rho\Big)^{\frac{1}{\rho}-1}\rho(1-\theta)C^{\rho-1}\frac{dC}{dH_t} \tag{46}$$

which in turn gives:

$$\frac{dH}{dC} = \Big(\theta T^\rho + (1-\theta)C^\rho\Big)^{\frac{1-\rho}{\rho}}(1-\theta)C^{\rho-1}\frac{dC}{dH_t} \tag{47}$$

this is the same as the RHS of (22), except for the minus in front (due to the $-H'_{H_t}$). The first part of this term is very similar to the utility function itself, only in the power of $\frac{1-\rho}{\rho}$ instead of $\frac{1}{\rho}$. These expressions will thus be similar if the utility function is in the power of $\frac{1}{1-\rho}$, as is stated in (22). If this change is made, and also inserted for $\frac{dC}{dH_t}$, the result will be:

$$\Big(u(T(t),C(t))\Big)^{\frac{1}{1-\rho}}(1-\theta)C(t)^{\rho-1}\alpha_h\omega_{h_o}x_h H_t(t)^{-(\alpha_h+1)}$$

i.e. the RHS of (22), which is:

$$\dot{\lambda}_b(t) - r\lambda_b(t) = -\Big(u(T(t),C(t))\Big)^{\frac{1}{1-\rho}}(1-\theta)C(t)^{\rho-1}\alpha_b\omega_{b_o}x_b(t)B_t(t)^{-(\alpha_b+1)} \tag{22}$$

By dividing (24) by λ_h and moving r to the RHS, the result will be (25)

$$\frac{\dot{\lambda}_h}{\lambda_h} = r - \frac{\Big(u(T(t),C(t))\Big)^{\frac{1}{1-\rho}}(1-\theta)C(t)^{\rho-1}\alpha_h\omega_{h_o}x_h(t)H_t(t)^{-(\alpha_h+1)}}{\lambda_h} \tag{25}$$

[51]The hydrogen case is calculated here, but the same is true for battery technology

if then substituting in for λ_h from (43), this gives (27):

$$\frac{\dot{\lambda}_h}{\lambda_h} = r - \frac{\big(u(T(t), C(t))\big)^{\frac{1}{1-\rho}}(1-\theta)C(t)^{\rho-1}\alpha_h\omega_{h_o}x_h(t)H_t(t)^{-(\alpha_h+1)}}{\big(\theta T(t)^{\rho} + (1-\theta)C(t)^{\rho}\big)^{\frac{1-\rho}{\rho}}\big((1-\theta)C(t)^{\rho-1}p_h(t) - \theta T(t)^{\rho-1}\frac{dT}{dx_h}\big)} \tag{27}$$

B The evolving of the shadow values of experience

For the λ_h to be non-negative (as it is assumed in this thesis), then the following must hold:

$$(1-\theta)C^{\rho-1}p_h \geq \theta T^{\rho-1}\frac{dT}{dx_h} \tag{48}$$

$$\implies (1-\theta)C^{\rho-1}p_h \geq \theta T^{\rho-1}\big((x_f+x_h)^{\eta}+x_b^{\eta}\big)^{\frac{1-\eta}{\eta}}(x_f+x_h)^{\eta-1} \tag{49}$$

This condition in turn, is difficult to state with certainty. As the consumption of non-transportation goods is weighted higher than transportation (as $\theta = 0.2$), and the price for hydrogen will be high in an initial phase when there is little gained experience, it seems reasonable to believe that the LHS of (48) and (49) are bigger than the RHS. A simple test using the simulation result, will be to plot the shadow values to see if this is non-negative. This is done based on (27) and (28) and the numbers are taken from the baseline scenario above:

$$\lambda_h = \big(\theta T^{\rho}+(1-\theta)C^{\rho}\big)^{\frac{1-\rho}{\rho}}\big((1-\theta)C^{\rho-1}p_h - \theta T^{\rho-1}\frac{dT}{dx_h}\big) \tag{27}$$

$$\lambda_b = \big(\theta T^{\rho}+(1-\theta)C^{\rho}\big)^{\frac{1-\rho}{\rho}}\big((1-\theta)C^{\rho-1}p_b - \theta T^{\rho-1}\frac{dT}{dx_b}\big) \tag{28}$$

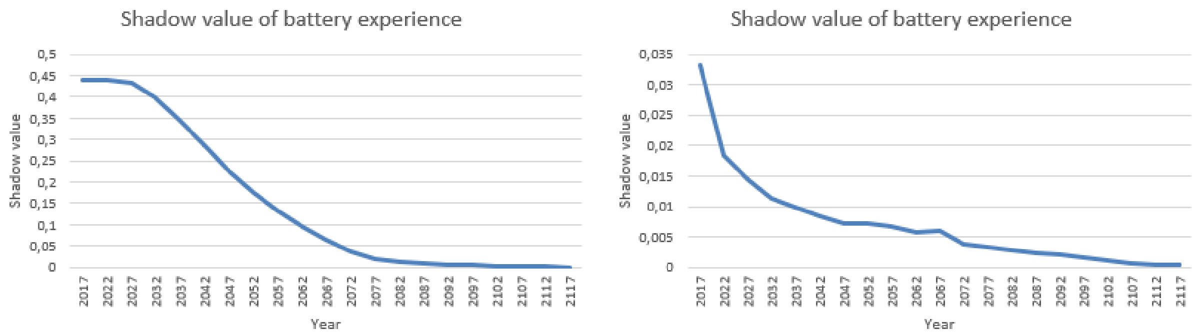

Figure 6: The shadow prices of experience

This shows that the values are non-negative, but move towards zero. This means that (48), and equivalently (49), holds in the simulations. The 'real' shadow values here, share the basic features of Figure 5 in section 5.4, as expected. It is also difficult to interpret the absolute values of the experience in the two technologies. Remembering the small values from section 5.4, this means that the even though the marginal value of experience is relatively high, as shown in Figure 6, the marginal utility gain (i.e. the whole term with λ's in (19)) are low.