ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis (Programme: Urban, Port and Transport Economics)

Assessing the potential of Green Hydrogen using learning curves from expert elicitation and the implications for the Port of Rotterdam

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Executive summary

Green hydrogen is predicted a large future role to decarbonize hard-to-abate sectors, while also to complement world-wide electrification. The port of Rotterdam aims to use this potential to kickstart a hydrogen economy, producing, using, importing, converting, and putting though low-carbon hydrogen. The potential of green hydrogen in the port is subjected to its economic viability and hence, by reaching the predicted substantially lower cost levels, resulting from with cost reductions of renewable energy, scale, and learning effects. This study focused on the final, and important endogenous cost factor – the learning effects - to determine the potential cost reductions of green hydrogen and what this implied for the port of Rotterdam.

Learning cure theory states that every product or technology has a constant learning rate, which gives the percental unit cost reduction each doubling of cumulative capacity, and hence, the theory states that cost reductions do not come with time, rather with increased production volumes. Learning curve has been frequently applied to renewable energy technologies. Additionally, it this learning-by-doing is sometimes expanded with learning-by-searching, other than just the usual learning-by-doing, making it a two-factor learning curve, while learning rates can also be determined on a component basis.

In determining the learning rate for green hydrogen this study encountered substantial disparities in the current and predicted cost levels for the different technologies. Therefore, this study first looked for the reasons behind the disparities, coming to the conclusion for this study to determine significant, up-to-date and state of the art learning rates, experts had to be consulted to provide for predictions for the cost reductions, structured as an expert elicitation. Furthermore, it was concluded that basing learning rates on investments cost only would not lead to meaningful results and thus, learning rates had to be based on levelized cost of hydrogen per kilogram, hereby enabling the inclusion of endogenous technological progress in other KPI's beyond investment cost, most importantly, system efficiency and flexibility. The electricity costs and total yearly input of electricity (load factor) were assumed variable to enable variations per source, region and future prices, and thus learning rates were to also vary with electricity price and load factor. To in turn be able come to strategic implications, the results were translated into different cases relevant to kickstart a hydrogen economy. For local production, using electricity from the grid and directly connected to Dutch offshore wind, while for large-scale imports, large-scale production from cheap solar electricity.

In general, the investment cost predictions of this study, EU's deployment targets, showed that costs of green hydrogen are to decrease more rapidly, under 300 €/kW before 2030, than predicted by older commonly used studies using, such as the IEA. This confirms that green hydrogen by increasing deployment with strong policy and policy mechanisms, can be produced at substantially lower cost levels. Additionally, the often-mentioned future superiority of the PEM technology was challenged by the results of this study, as Alkaline showed a significantly steeper learning curve, mostly due to PEM limitation with its high use of precious metals. Moreover, Alkaline has recently made substantial technological progress not only affecting investment cost, but also other KPI's.

The learning rates showed a significant variation with and dependence on electricity price and load factor. For Alkaline electrolysers the learning rate ranged from 3 to 16%, while for PEM electrolysers it ranged from 3 to 10%. This was confirmed by the with cost reductions increasingly larger contribution of electricity costs to the levelized cost of green hydrogen, around 70 to more than 90%. This showed the increasing dependence on electricity cost and load factor, and hence, the significance of improvements in system efficiency and flexibility, especially with the reduced future investment costs.

The results from three different cases showed, among others, the potential or even necessity of system flexibility and integration with offshore wind, to capture more electricity at lower prices. The SOEL technology showed most potential in the grid-connected cases where the advantage of higher efficiency is stronger with higher load factor and electricity prices. The import case resulted in significantly lower levelized costs of hydrogen when produced at large scale taking advantage of cheap Solar PV electricity prices.

For the port of Rotterdam, the overall results on the costs implied that **for producing green hydrogen from Dutch offshore wind, energy efficiency, system flexibility and upstream integration is needed to complement the electricity system and to not further inflate demand for the elsewhere much needed renewable electricity**, at least until massive expansion of offshore wind. The SOEL technology's high learning rate for grid connected electrolysers, showed its potential to be deployed for production of e-fuels, combined with the in Rotterdam abundant CO_2. The case on large scale imports showed already low levelized cost levels, implying a large potential, however, the resulting importance of transport cost make future overseas transport unattractive compared to cheaper pipeline transport. This can for instance be green hydrogen from cheap solar PV energy in the South of Spain or Portugal, hence, surpassing the port of Rotterdam. Hereby, the three cases showed the potential, but also the limitations of green hydrogen in the port of Rotterdam. **Thus, although the potential of green hydrogen is great, especially in the port of Rotterdam, it needs to be applied in the right ways which in the end benefit, and not hamper, a fast and low-cost road to carbon neutrality by 2050.**

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List of abbreviations

AEL	Alkaline Electrolysis
AEMEL	Anion Exchange Membrane electrolysis
CAPEX	Capital Expenditures
CCUS	Carbon Capture, Utilisation and Storage
LC	Learning Curve
LCOE	Levelised Cost of Energy
LCOH	Levelised Cost of Hydrogen
LR	Learning Rate
PEMEL	Proton Exchange Membrane Electrolysis
PV	Photovoltaic
RES	Renewable Energy Source
SOEL	Solid Oxide Electrolysis

1. Introduction

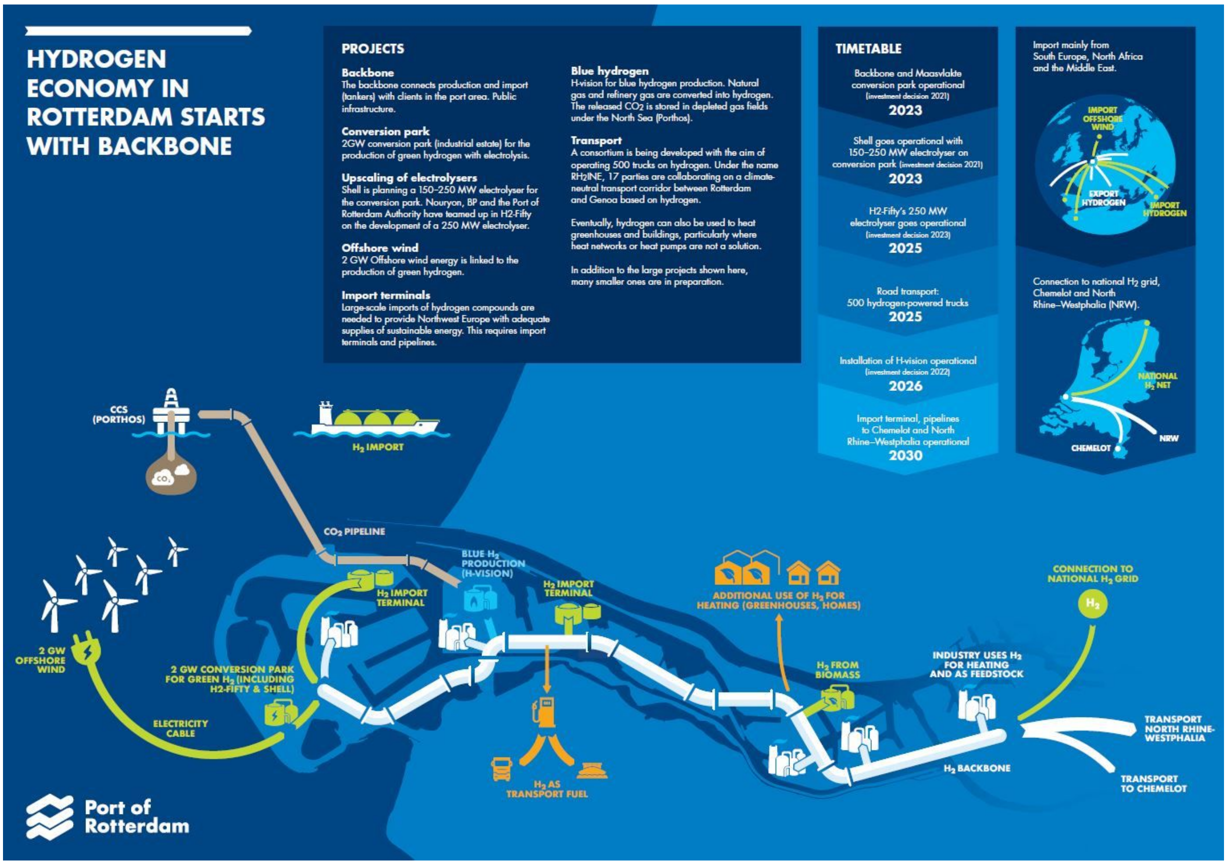
1.2 Contextual background

The world is in a transition to decarbonise and limit global warming well below 2 degrees, pursuing efforts to limit it to 1.5 degrees. This transition to reach the 2-or even 1.5-degree scenarios, targets set out by the United Nations's COP-25 Paris agreement on mitigating climate change, seems problematic for number of sectors which are harder to abate or electrify. In these sectors, such as the chemical, industrial heating, heavy-duty trucking, aviation and shipping sector, an increasingly bigger role is assigned to green hydrogen, together with is potential to complement renewable energy sources and transport.

The vast majority the hydrogen produced today is fossil-based, mainly using steam methane reforming (SMR) and to a smaller extent, coal gasification, commonly defined as *grey* hydrogen. However, when part (80-90%) of the emitted CO_2 in these processes is captured and subsequently stored or used (CCUS), it becomes low-carbon hydrogen, referred to as *blue* hydrogen (IRENA, 2019). *Turquoise* hydrogen, which is produced using methane in the pyrolysis process emitting solid carbon instead of CO_2, provides for another low-carbon emitting option (TNO, 2020). In water electrolysis, water is split in hydrogen and oxygen, using electricity from a renewable energy source (RES), the hydrogen produced is called *green* hydrogen. This carbon-free hydrogen can complement renewable energy sources and provide seasonal storage, be used as a fuel in fuel-cell vehicles, replace grey hydrogen in the industry, be blended in with natural gas, while it also can be converted into for instance ammonia, methanol or synthetic fuels, to decarbonize the aviation or shipping sector at the same time enabling overseas transportation. Hereby, it is also referred to as Power-to-X, where the 'X' can thus stand for a wide range of the applications of green hydrogen. The wide range of applications, the expected investment cost reductions, technologic progress, while also the reduction in costs of electricity of renewable sources, all give rise to the current momentum of green hydrogen, the main topic of this study.

The momentum of green hydrogen is clearly visible as shares of hydrogen producers and manufacturers are soaring, with shares of some fuel cell producers even rising as far as 342% in 2020 (Sanderson, 2020). Moreover, in five months up to April 2020, the green hydrogen projects in the pipeline in the EU more than doubled from 3.2 to 8.2 GW of total capacity (European Commission, 2020). Meanwhile, governments all over the world are adding to this momentum. The recently announced hydrogen strategy of the European Commission adds to this by setting very ambitious targets of installing 40 GW of green hydrogen capacity by 2030 (European Commission, 2020). The Dutch government wants to become a world leader in production and use of low-carbon hydrogen using its unique starting position, with its extensive existing gas infrastructure, and also aims at a global market for green hydrogen (Janssen, 2020). More locally, the port of Rotterdam to become a i) production, ii) import, iii) trading and iv) usage hub for blue and green hydrogen, which is illustrated by the fact that recently, it was the first port which joined the Hydrogen council, the industry association which intends to kickstart the hydrogen economy. The roadmap found below in in Figure 1 further illustrates the strongly diversified ambitions of the Port of Rotterdam, starting a hydrogen economy with blue hydrogen and eventually transitioning to green hydrogen production, imports, throughput and usage.

Figure 1: Roadmap of the Port of Rotterdam to start the Hydrogen economy



Another region in the Netherlands with possibly the most ambitious plans for a hydrogen economy is the north, for which a total of €9 billion of investments related to hydrogen is expected in the region, following the phasing out of natural gas, this region so depends upon. Gas was found in Slochteren in 1959, which gave name to the "Dutch Disease" phenomena, while it is now causing earthquakes in the region, which has led the shift from grey natural gas to green hydrogen gas, emphasized by the following figure from Gasunie (2020a).

Figure 2: Indicative view of planned 2030 hydrogen ecosystem in 2030

Source: Gasunie (2020a)

In terms of production, the Port of Rotterdam plans to increase production by reserving 2 GW's of offshore wind capacity for green hydrogen by 2030, and another port area in the Netherlands, Groningen Seaports, plans to exceed this the Groningen Seaports this by installing 3-4 GW's of input capacity by 2030, also from offshore wind, together with Shell and Gasunie. Remarkably, this would mean 15% of the total green hydrogen production capacity in the EU by 2030 being based around two port areas in the Netherlands, although it should be noted that these plans are currently in an earlier phase and require substantial capacity increases in Dutch offshore wind energy.

The ambitious targets to kickstart the hydrogen economy with the different hubs of the Port of Rotterdam are based on the general consent that production costs of green hydrogen are set to fall sharply, offsetting a worldwide low-carbon hydrogen economy.

The underlying reasons for these predicted cost reductions are, similarly to other renewable energy technologies such as solar PV and wind energy, found in scale and learning effects (Hydrogen Council, 2020) (IEA, 2019) (IRENA, 2018) (Schmidt et al., 2017). While the former is more straightforward, the latter is less obvious, yet result from a widely used concept, the learning curve. Learning curve theory states that accumulated experience leads to unit cost reductions, against a constant learning rate with each doubling of accumulated production, described by MacDonald & Schrattenholzer as (2001):

"*For most products and services, it is not the passage of time that leads to cost reductions, but the accumulation of experience. Unlike a fine wine, a technology design that is left on the shelf does not become better the longer it sits unused*".

Hence, when deriving a learning rate, adoption speed and timing are factored out and it provides for a different approach, which shows the cost reductions possible when production accumulates in a growing green hydrogen economy. Also, recent developments in hydrogen from water electrolysis show green hydrogen is the perfect example, as it had sat unused on a shelf after being a more common technology mid 20th century and the technology already exists more than 200 years (Santos et al, 2013). Learning curve theory provides the foundation for the future of green hydrogen and hence, developing learning rates for green hydrogen production will be the main focus of this study.

1.3 Research Aim and Questions

The aim of this research is to analyse the production costs of various green hydrogen technologies by making use of learning curve theory in order to draw strategic implications for the Port of Rotterdam's hydrogen agenda. As previously mentioned, learning curve theory is the foundation of the projected cost reductions and hence, is the foundation potential of green hydrogen. This leads to the following central question, which this study tries to answer:

"What is the learning curve of green hydrogen production and how does it impact the ambitions of the port of Rotterdam?"

The central question has the following sub questions, which will be answered in chapters 2 to 6, respectively.

A. Why does this study apply learning curve theory?
B. What are the expected cost reductions in literature and how do these align with learning curve theory?
C. How will the learning rates for green hydrogen be determined?
D. What are the learning rates for green hydrogen technologies and what do they?
E. What are the strategic implications of the findings in for the ambitions of the port of Rotterdam to kickstart different hydrogen hubs?

1.4 Operationalizing the (sub)questions

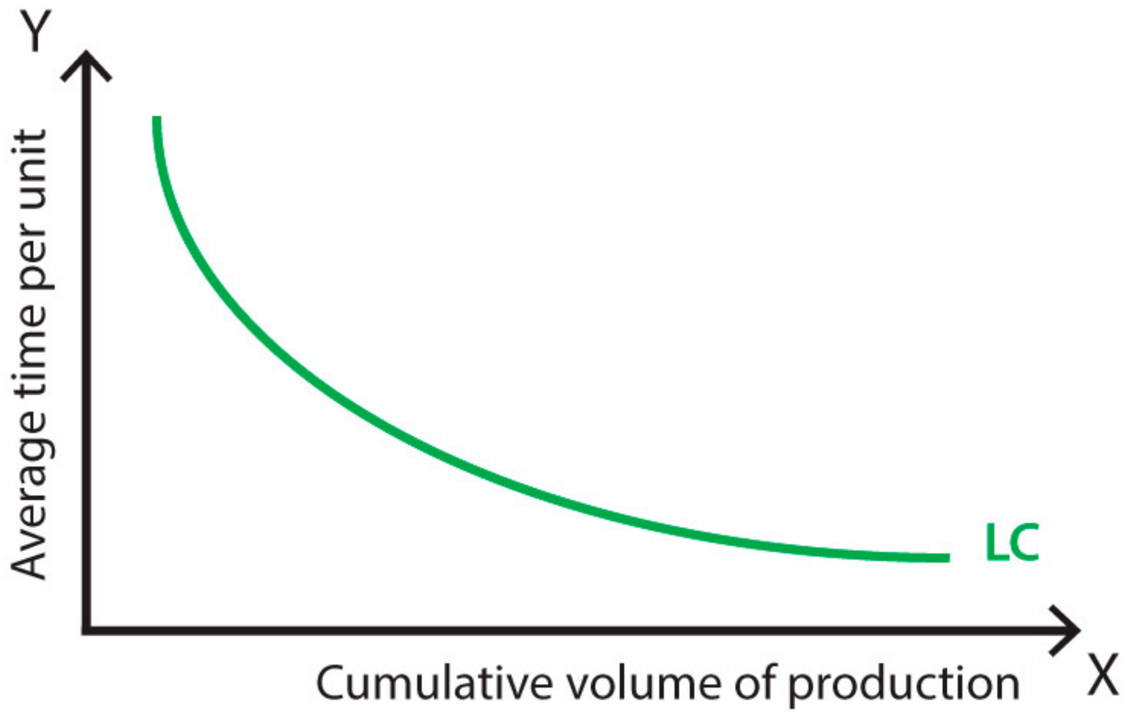
In chapter 2, first the questions what learning curve is and how it applies to energy technologies, need to be answered, as learning curve theory provide grounds for the potential of green hydrogen. In chapter 3, green hydrogen is further introduced, analysing predictions on the potential and costs in current literature. Hereafter, problem arisen from the differences in predictions are presented and solutions for these problems are proposed coming back to learning curve principles and introducing expert elicitation and levelized costs as a way to establish learning rates. In chapter 4, first assumptions on levelized cost are stated, which lead to the uncertain parameters for which the expert panel is consulted. The specifics of the expert elicitation survey and interviews are then discussed. In chapter 5, The learning rates based on levelized cost of hydrogen are presented and hereafter, these findings are signified by applying it to cases, hereby also absolute values of levelized costs of hydrogen are presented. In chapter 6, the findings in chapter 5 are combined with the Port's ambition to start the hydrogen economy with a i) production, ii) import, iii) trading and iv) usage hub. These hubs are based on the current businesses and strengths of the port, where the production hub is based on the favourable carbon capture use and storage environment for blue hydrogen and the offshore wind potential in the North Sea area to the port for green hydrogen (Figure 1: Roadmap of the Port of Rotterdam to start the Hydrogen economy. The import and trading hub role for hydrogen is similar to the current fossil-based powerhouse role of the Port of Rotterdam. For this hub the port wants to profit from possible future hydrogen pipelines, comparable to the current role of the inland waterways, and other existing infrastructure in the hinterland to convert, trade and transport into the hinterland hydrogen imported from renewable energy abundant regions. The usage hub is based on the fact that many of the hard-to-abate sectors where green hydrogen has potential are located around the ports. These hubs reinforce one another and developing these hubs simultaneously, the port can develop a strong hydrogen position on a global level (Drift, 2020).

2. The learning curve

2.2 Introduction to learning curves

The learning curve made its way into economics in 1936, when Paul Wright studied the aircraft industry by plotting the average time spent on producing an aircraft against cumulative production. Wright discovered that with each doubling in cumulative capacity, the unit cost or labour time decrease with a constant percentage, described as the learning rate (Wright, 1936). This effect, also known as learning-by-doing, shows how accumulating production experience leads to cost reductions. Product or technologies can differ in their ability to learn and hence, can have a different learning rate. In figure 1, a typical learning curve is presented, which at lower cumulative capacity levels shows a steep downwards curve, thus representing relatively large marginal unit cost reductions. As cumulative capacity increases, doublings of cumulative capacity occur less frequently and hereby, the learning curve flattens.

Figure 3: Basic example of Wright's Learning Curve



Source: Polinomics

Using the power law, the learning curve is presented by the following equation (Loerch, 2013):
Equation 1: Wright's Learning curve

$$C_t = C_0 Q_t^{-\varepsilon}$$

$With:$

$C_t = Cost\ or\ labour\ hours\ per\ unit, in\ year\ t$

$Q_t = Cumulative\ production, in\ year\ t$

$\varepsilon = Elasticity\ of\ learning\ (learning\ index), also\ the\ slope, defined\ as:$

$$-\frac{\log(learning\ rate)}{\log(2)}$$

Henderson at The Boston Consulting group later applied a similar, but more macroeconomic approach to a broad scope of products, renaming it as the *experience curve*, with the main difference of deriving the learning rate from prices instead of costs (BCG, 1970). Both showed unit cost reductions with each doubling of accumulated production, Henderson quantified this learning rate for the range of products studied between 20% and 30%, while Wright similarly concluded a learning rate at around 20% for aircraft production.

2.3 Learning curve in energy analysis

The learning curve theories have also become increasingly common in energy system models when predicting future costs for energy technologies (Söderholm & Sundqvist, 2007). The learning curve concepts, sometimes rebranded as technology learning or endogenous learning to analyse cost developments have been used frequently when analysing the cost developments of Photovoltaic (PV) and Wind energy (sources). More recently, also the cost developments of different energy carriers, such as green hydrogen, their applications and technologies were assessed using technology learning or experience curves (sources). Moreover, the learning curve concept has also laid the foundation for the *push* and the *pull* strategy of the EU, incentivizing new clean technologies along their cost reduction development curve (Joint Research Centre, 2012). Several improvements were proposed to overcome issues or to provide for a more extensive analysis, the two most commonly proposed improvements, respectively the component-based approach and the two-factor learning curve, are explained below.

2.3.1 Component based learning curve

In this approach, used by Ferioli et al. (2009) and Van der Zwaan et al. (2011), different cost components of the researched technology are separated into components which can and cannot learn. In this way, for technologies with a lower maturity or technology readiness level, a better fit of the data can lead to a higher significance of learning rates (Böhm et al., 2019)

(Joint Research Centre, 2012). Furthermore, in this approach each cost component can also be assigned a specific learning rate. This approach is, however, subjected to the data available and the cost data per component is sensitive information to share for companies. In addition, issues can arise when innovations lead to replacement or complete omittance of a cost component.

2.3.2 Two-factor learning curve (TFLC)

The traditional learning curve, as presented in equation 1, assigns cost reductions to a single explanatory variable, cumulative capacity and thus, incorporates solely the learning-by-doing effect. Yet, in many cases a different approach, which also incorporates other potential drivers of cost reductions, is required. In example, policy makers or companies, when allocating funds, can demand a quantitative assessment of the effect of investments in research and development (R&D) (Joint Research Centre, 2012.) Kouvaritakis et al. (2000) presented a solution by adding a learning-by-searching effect to the existing model in equation 1, which, by analogy, are the cost reductions following a doubling in R&D investment. This leads to the two-factor learning curve, with the two factors being cumulative capacity and cumulative R&D investments, or respectively, learning-by-doing and learning-by-searching. By separating between a learning-by-doing and learning-by-searching rate policymakers can establish a strategy to efficiently allocate funds per technology, either favouring deployment or investments in R&D. However, a major issue is the inability to separate cost reductions either coming from learning-by-doing or learning-by-searching, which also translates when deriving the learning rate in regressions. This was exemplified by the Joint Research Centre (2012) in an input note on the Danish policy and resource mobilization in wind energy. The Danish, in an early stage of wind energy development, focused on commercializing wind turbines next to research, development and demonstration (RD&D), which was the main focus of Germany. The resulting commercial experience led to technology development, innovations, deployment and cost reductions in Denmark using a significantly lower relative RD&D budget. The impact of this is still clearly visible today, with Danish company Vestas being the top producer of wind turbines world-wide, and with the second largest player in the market, Siemens Gamesa, partly originating from a Danish company (Wood Mackenzie, 2020). This example shows that RD&D budgets do not negatively affect unit costs and increase technology development and hereby in this case, separating learning-by-searching from learning-by-doing is problematic.

2.4 Learning curves for energy technologies: Empirical Issues

As shown above, improvements can add value and solve existing issues of the learning curve, whilst on the other hand resulting in new issues. Söderholm and Sundqvist analyse the empirical side of these issues and their study can be seen as a foundation for the empirical technology learning curves for energy practices, serving as a guideline for learning curve implementation in energy models (2007). Their paper provides an extensive comparison of the different models for applying learning and experience curves to renewable energy technologies, based on wind energy from Germany, Denmark and the United Kingdom. Söderholm and Sundqvist start with the basic one-factor model, then add scale effects and hereafter, derive the two-factor model from a standard Cobb-Douglas[1] function. Finally, different two-factor models follow when correcting for endogeneity, resulting from simultaneity and omitted variable bias. Based on this, the paper concludes a number of recommendations, which this study will carefully adhere to when developing the learning rates for green hydrogen and Power-to-X. A brief summary of the empirical issues is provided below.

Söderholm & Sundqvist (2007) highlight four issues when estimating learning rates:

1. *Choice of dataset and definitions*

   Removing outliers or early observations from the dataset, defining the variables and choosing the time period all affect the learning rate heavily and hence can lead to different learning rates, using the same starting dataset.

2. *Operationalization*

   The question is if the positive trend of cumulative capacity really does capture learning-by-doing, or just an exogenous technological process, such as global automation, and robotization and this similarly holds for learning-by-searching and R&D knowledge stock.

3. *Endogeneity and Simultaneity*

   The basic learning curve models assume that cumulative capacity is an exogenously determined variable and that the technology becomes cheaper due to higher cumulative capacity. On the other hand, investors invest and expand capacity of the energy technologies because R&D and learning lowers investment costs and

[1] Widely used production function depicting the relationship between two input (Capital and Labor) factors and the output factor

therefore, the variables are simultaneously determined. Simultaneity leads to a biased and inconsistent learning rate and consequently needs to be controlled for, which is not always the case.

4. *Omitted variable bias*

   Omitted variable bias occurs when important explanatory variables are left out of the model, more specifically a variable which is a determinant of the independent variable and is correlated with the dependent variable. In this case it is clear to see that costs are affected by other variables which also correlate with cumulative capacity and R&D, most notably input prices and scale effects. Not controlling for these variables would lead to a positive bias in the learning rate. Besides, a different variable, which can be even harder to control for, is the impact of policy. This is for instance the implementation of feed-in-tariffs, which impact both the energy price and cumulative capacity.

Söderholm & Sundqvist (2007) also present solutions for these issues, these guidelines consist of datasets and this strengthens the need for a complete data. Summarizing, the guidelines consist of including a sensitivity analysis, a time trend test, a statistical test for technology diffusion and including, amongst others, scale effects to test for omitted variable bias. All of these guidelines emphasize the need of an extensive dataset, containing not only R&D, cumulative capacity and cost variables, but also instrumental variables and variables such as scale effects, input prices and policy measures to prevent for omitted variable bias. These recommendations will be carefully adhered to when developing learning rates for green hydrogen.

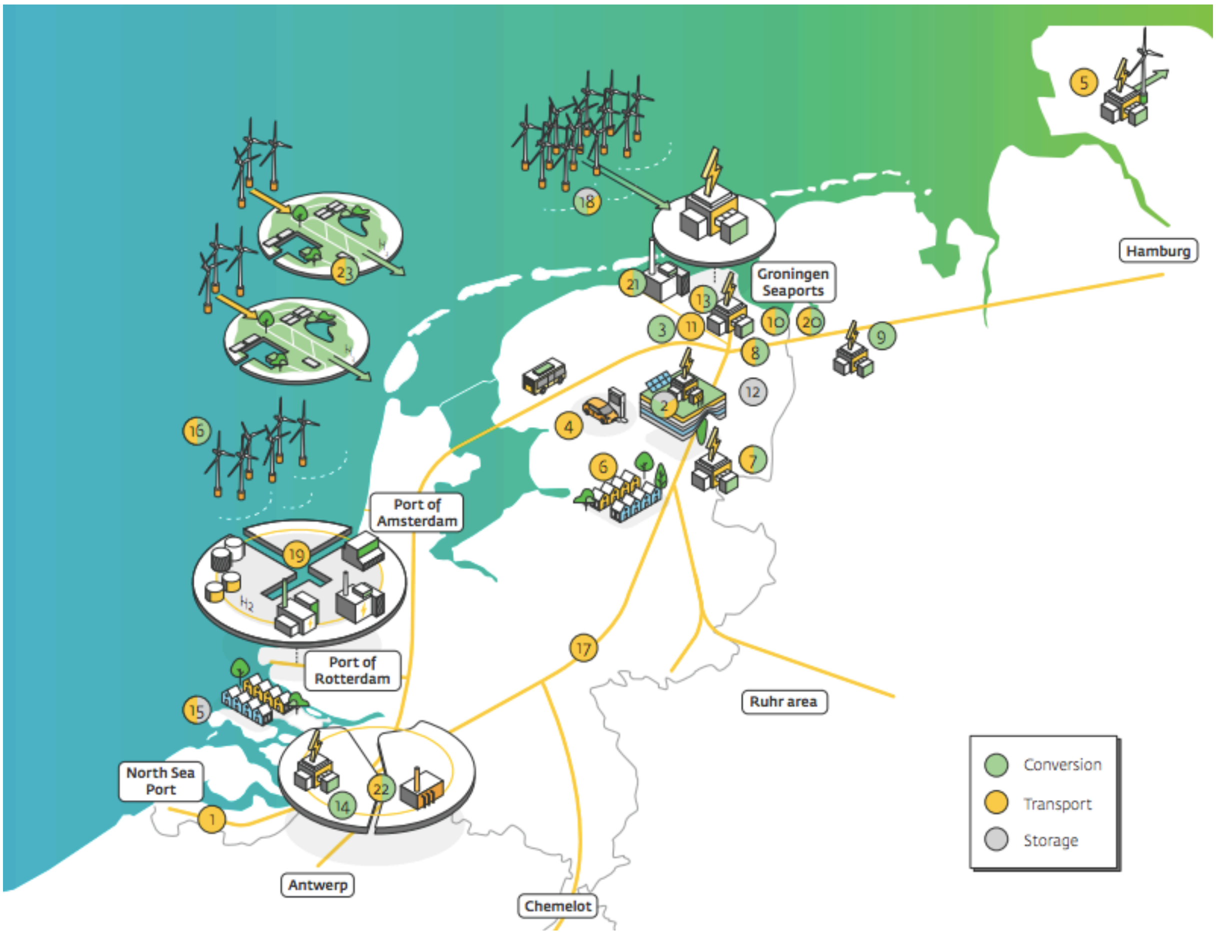
3. Green hydrogen

3.2 History and future of green hydrogen

The chemical process of splitting water in oxygen and hydrogen using electricity, called water electrolysis, has already been around for more than 200 years. The commercialization was induced by the invention of the Gramme machine in 1869 and the “golden age” of electrolytic hydrogen development followed between 1920 and 1970 (Santos et al, 2013). Since mid 20th century already large-scale electrolysers of up to 165 MW were deployed (IEA, 2019) mainly in the ammonia fertilizer industry. In these years, electrolytic hydrogen profited from the steady load and the low-cost of hydropower. In 1966, General Electric developed a new type of water electrolyser, Polymer Electrolyte Membrane electrolysis (PEMEL), to overcome the drawbacks of the incumbent Alkaline electrolysis (AEL) technology, mainly relating to low system flexibility to handle and react to fluctuations in the electricity supply (Shiva Kumar & Himabindu, 2019). However, the exploitation of energy from fossil sources ceased the progress into hydrogen from water electrolysis, as coal gasification and natural gas reforming provided a low-cost alternative option, starting the development into the large market it is today. Driven by an energy transition away from the fossil energy sources and the cost reductions of renewable electricity, green hydrogen is assigned a bright new future. This also led to the introduction of new technologies, high temperature or Solide Oxide electrolysis (SOEL), which is highly efficient where steam is available, and this technology can be used for co-electrolysis for the production of e-fuels. More recently, a new technology emerged called Anion Exchange Membrane electrolysis (AEMEL), aiming to combine the best of the AEL and PEMEL technologies. The focus of this study will lie on the most mature technologies - AEL and PEMEL. Whereas SOEL and moreover AEMEL are currently on a lower technology readiness level, although both are still frequently touched upon. The bright future of green hydrogen also presents in the varieties roles it can play. In seasonal energy storage, complementing renewable energy sources, in mobility, for fuel cell vehicles and as a basis for synthetic fuels, in several industrial and chemical processes, as a basis for, among other things, ammonia, methanol, industrial heat in for instance steel production. A major part of these applications is located around ports and industrial port complexes in the Netherlands, where most of the current Dutch Hydrogen demand originates from, which in turn is ±15% of current EU hydrogen demand (FCH Observatory, 2020). Moreover, in the future industrial hydrogen can be transported by pipeline to industrial clusters in for instance Germany and

Belgium, where steel production and heat in the chemical sector can lead to substantial future hydrogen demand. In the following figure from Gasunie (2020), this idea is visualised.[2]

Figure 4: Gasunie - Moving towards hydrogen in 2030 and 2050



Source: Gasunie (2020b)

3.3 Government incentives and limitations

As history shows, the potential of green hydrogen is heavily subjected to its economic viability. The introduction of government incentives, which can be in the form of subsidies, taxation of fossil-based alternatives, but also carbon cap and trade systems, can make way for cost competitivity of green hydrogen as a low carbon alternative. Especially the carbon 'cap and trade' can already allow for cost competitivity, such as the emissions trading scheme (ETS) in the EU, which shortly are different market systems based on putting a 'cap' on a company's carbon emissions and when this "cap" is exceeded, the company needs to trade and buy emission allowances from companies, which did not reach their "cap", leading to a

[2] This is only part of the figure, full figure also shows ongoing hydrogen projects and can be found in the source mentioned in the references.

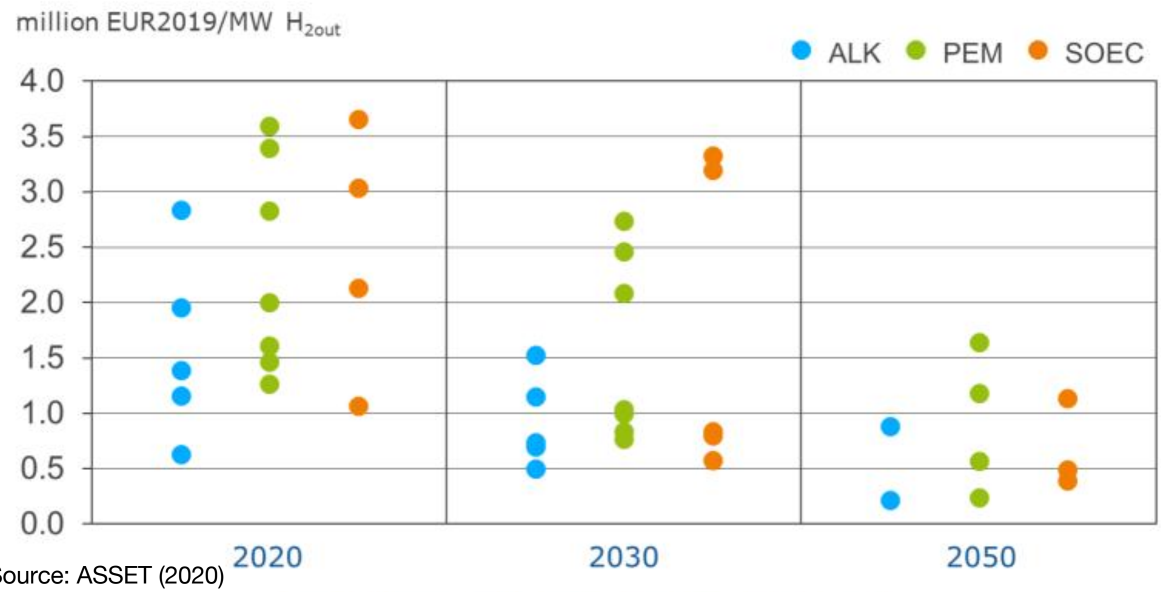
trading scheme with a resulting carbon price (EU ETS, 2017). The increasing importance of such a system is illustrated in Tesla Automotive' recent quarterly results, where 7% of revenues resulted from selling emission allowances to industry competitors (CNBC, 2020). Such systems, similar to for instance the SDE subsidy schemes in the Netherlands, induce companies to decrease emissions, but at the lowest cost possible and thus to seek the solution with the lowest 'carbon abatement cost'. For green hydrogen, this means again a focus on reducing costs, and those cost reductions, by learning curve theory, come with increases in cumulative capacity. Government policy is further discussed in the final chapter in this study.

At the same time, next to the costs, it is critical to also acknowledge the limitations of green hydrogen and the main limitation relates to the renewable electricity needed for the production of green hydrogen. Green hydrogen production requires more electricity than it produces in hydrogen equivalent due to energy lost in the process. This green electricity is also much needed elsewhere in, for instance, the Netherlands, where only 18% of consumed electricity was generated from renewables in 2019 (CBS, 2020). Therefore, in regions such as the Netherlands, renewable electricity used to produce green hydrogen is in turn not used to decarbonize the still mainly grey energy systems. Here, green hydrogen needs to prove it is the only low-cost option in its potentially hard-to-abate end-use sectors to be able, thus providing for the lowest abatement costs, to claim a share of renewable electricity. This, of course, does not hold in cases where green hydrogen is produced complementing renewable energy sources and the electricity grid, by capturing otherwise curtailed energy and providing seasonal storage and transport. Nonetheless, in both cases, usually referred to as grid-connected and off-grid, green hydrogen needs to show its potential as a low-cost decarbonization option. Thus, the leading first step is to analyse the investment costs of the different electrolyser systems and these are by many expected to decrease substantially along the learning curve (Hydrogen Council, 2020). As will be shown later in section 3.6, it is to be seen the first of several steps, as looking beyond investment costs is of great importance. In the Findings, differences between grid and off-grid systems are discussed in further detail, adding a quantitative assessment.

3.4 Disparity in investment costs predictions

In literature the general consensus is that production costs of green hydrogen will reduce, however, an analysis of literature and data on the investment cost of green hydrogen shows a large disparity in presented data. Different studies all claim different cost, cost reductions and timing of cost reductions. The figure below (ASSET, 2020), shows how scattered the predictions from different sources are, with for instance the most mature water electrolysis technology, Alkaline, differing by a factor of five in 2020. This figure shows data points from recent studies, normalised to millions of euro per capacity of hydrogen output in megawatt. By presenting investment costs in hydrogen output, instead of the usual electricity input, efficiency of the system can be incorporated to provide for a more complete assessment.

Figure 5: Investment costs for green hydrogen production technologies



Source: ASSET (2020)

The discrepancies in literature on the current and future costs, shown in the figure above, critically complicate the assessment of the learning rates of hydrogen and hence, the potential of green hydrogen. Therefore, it is good practice to first address the reasons behind the discrepancies, which lead to the different solutions and concepts necessary to accurately sketch the potential of green hydrogen. Four main reasons or problems for the discrepancies are explained, following the hypotheses that costs predictions diverge, resulting from:

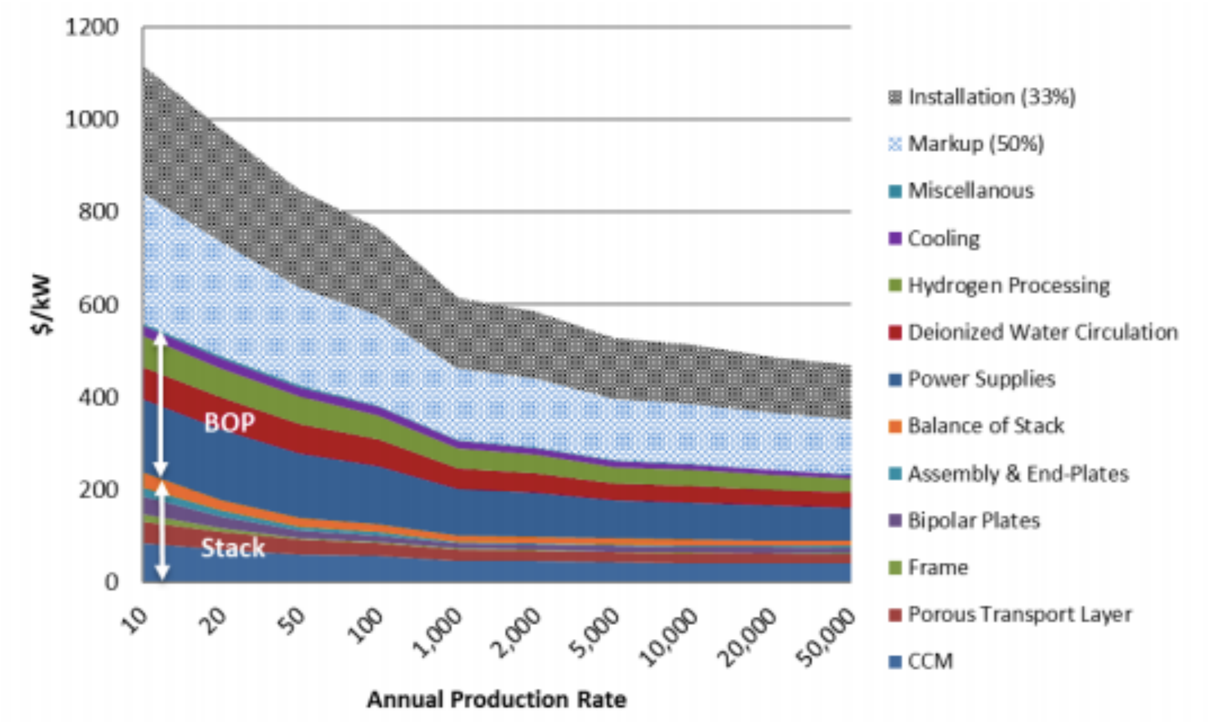
A. System boundaries are not or poorly defined
B. The focus is too much on investment costs
C. Used sources are recycled and outdated
D. Discussions on the speed and timing of adoption/deployment

The first two reasons relate more specifically to green hydrogen, while the last two reasons also highlight broad underlying problems about the analysis of renewable energy technologies.

3.5 Defining system boundaries

First, one clear reason for the disparity in the data is the difference and lack of defining the system boundaries, as besides the basic electrolyser stack, the system includes a balance of stack, the balance of plant, and power electronics part. All which can make up a significant part of the costs and can include or exclude different parts. The cost breakdown of a 1MW PEMEL system in the figure of Mayyas et al., (2018) below, shows the great impact excluding one of those aspects would mean for PEMEL.

Figure 6: Cost breakdown 1 MW PEMEL system



Source: Mayyas et al. (2018)

An underlying reason for differentiation in the system boundaries is that feedstock input and hydrogen output can differ in form. Electricity input differentiates in either alternating or direct current (AC or DC), water input in terms of purity or salt content and hydrogen output in terms of output pressure and purity. Grid electricity is usually AC, which would mean needing a rectifier to transform it to DC, while water may need purification or desalination and hydrogen output may need purification and compressing. Adding a rectifier, water or hydrogen purifier and compressor comes at a cost and thereby, the question is what each datapoint assumes as input and output and what it includes as part of the electrolyser system.

Most studies, if at all, only partly clarify what their investment cost include. Subsequently, this can lead to comparing different systems, and therefore, to comparing apples with oranges.

3.6 Looking beyond investment costs

Most studies, focus on investment cost when assessing the potential cost reductions of green hydrogen, in Figure 3 efficiency was included by assessing capacity in hydrogen output instead of electricity input, which is a first step. Next to investment costs, a usually mentioned cost factor are the operating expenditures, which is mostly taken as a percentage of the yearly capital expenditures and thus relates to the investment costs. However, by only focusing on investment cost, other factors which influence the production cost indirectly, are ignored. Below in table 1, the most important KPI's, besides operating and capital expenditures, are summarized based on data from the Hydrogen Council (2020), interviews with electrolyser manufacturers, company brochures and load flexibility on IEA's future of hydrogen (2019). The assumptions and system boundaries, of which the importance was explained in the previous section. Hereafter, the KPI's are discussed, which is also critical, as the relevance of each KPI can differ substantially per case.

Table 1: KPI's green hydrogen technologies (Hydrogen Europe, 2020) (IEA, 2019)

	AEL	PEMEL	SOEL	AEMEL
1. Efficiency	67%	61%	83%[3]	61%
2. Efficiency degradation (%/1,000hrs)	0.12	0.19	1.9[4]	>1.0
3. Hot idle ramp up (sec)	60	2	600	30
4. Cold start ramp up (sec)	3.600	30	43.200	1.800
5. Footprint (m2/MW)	100	60	150	90
6. Load flexibility (% of nominal capacity)	10-110	0-160	20-100	-
7. Current density (A/cm2)	0.6	2.2	0.6	0.8
8. Use of critical raw materials as catalysts (mg/W)	0.6	2.7	-	1.7

Source: Hydrogen Europe (2020), only load flexibility from IEA (2019), confirmed and adjusted in interviews with electrolyser manufacturer and the electrolyser' brochures

[3] Energy needed for steam generation is not included, as this usually available, when not available efficiency of SOEL would come down to 67%.
[4] Degradation at thermo-neutral conditions in percent loss of production rate (hydrogen power output) at constant efficiency, this is different than the definition for the other lower temperature technologies, since high-temperature SOEL faces material degradation due to the high termperatures

Assumptions, from Hydrogen Europe (2020a), except for (6), from the EA (2019):

0) *Input of AC power and tap water; output of hydrogen meeting ISO 14687-2 at a pressure of 30 bar and hydrogen purity 5.0. Correction factors may be applied if actual boundary conditions are different*
1) *Electrical efficiency at nominal hydrogen production rate of the system at standard boundary conditions*
2) *Stack degradation defined as percentage efficiency loss when run at nominal capacity.*
3) *Time required to reach nominal capacity in terms of hydrogen production rate when starting the device from hot idle (warm standby mode - system already at operating temperature and pressure).*
4) *Time required to reach nominal capacity in terms of hydrogen production rate when starting the device from cold standby mode.*
5) *Average specific space requirement of a MW system comprising all auxiliary systems to meet standard boundary conditions) and built up as indoor installation.*
6) *Load flexibility is the percental difference the system is able to differ from its nominal load, reported values should be seen as highly dependent on multiple other factors differing per system.*
7) *Mean current density[5] of the electrolysis cell running at operating temperature and pressure and nominal hydrogen production rate of the stack*
8) *Raw materials used in the catalysts in the stack:*
    a. *AEL: ruthenium for the cathode (mostly as RuO2)*
    b. *PEMEL: iridium as the anode catalyst and platinum as the cathode catalyst (Also, titanium is used in the Anode)*

3.6.1 Efficiency and efficiency degradation

For the production of green hydrogen, the two basic feedstock inputs are water and electricity and mainly the latter can play a significant role in the final cost of green hydrogen (Hydrogen council, 2020). The energy use needed for a kilogram of hydrogen can differ per system and is usually expressed in the efficiency – output of hydrogen divided by the electricity input of the complete system. This efficiency degrades with usage[2] and besides for SOEL, in green hydrogen production to keep a steady level of output, electricity usage is increased as

[5] This KPI is very important for the manufacturers, influencing many of the other KPI's, yet is not discussed here because the other KPI's which its influences are discussed extensively

degradation increases. Efficiency degradation is often limited by replacing the stack of the electrolysers on a certain time frame, generally once every 10 years for AEL, which of course comes at a cost as well. In table 1, the differences between the systems are clearly visible

Improvements in both efficiency and efficiency degradation can positively influence green hydrogen cost and with decreasing investment cost this effect becomes more important. The hydrogen council even states that by 2030 electricity cost will amount to 80% of the total cost of green hydrogen (2020). The importance of system efficiency and its degradation can result in a higher demand for systems with higher efficiency, even if the customer faces higher investment costs for those systems. For electrolyser manufacturers it can also be seen as a trade-off, where efficiency improvements can come at the cost of higher capital expenditures. Moreover, when a certain capital expenditures target cost reduction is reached the focus might shift to improving efficiency. This can undermine the importance of investment costs, and when relating this to the learning curve theory, it can also undermine the significance of relating learning-by-doing to investment cost. Ferioli et al., (2009) when faced by similar problems for the production of ammonia with scattered investment costs, even found more significant learning rates bases on system efficiency than on investment costs.

3.6.2 System flexibility: load flexibility and ramp up times

Another important factor or key performance indicator the ability of the system to handle lower or higher capacities of electricity input than its design capacity, for a certain period of time. This is crucial in the foreseen roles of green hydrogen complementing renewable energy sources, providing seasonal storage and flexibility in for instance periods of low or high winds or cloud formation, or in cases where supply-demand gaps lead to low or even negatively priced electricity. More flexible systems would allow the capture of otherwise (economically) curtailed electricity from renewable energy. Absorbing intermittent energy with flexible electrolyser systems shows a great potential with the expected rise of installed wind and solar energy capacities. In order to do this, electrolyser systems would need to allow for a longer period of flexible input electricity loads, which is seen as a main advantage of a PEM over an Alkaline system, for which a longevity of low or variable loads would stress and degrade the electrochemical system (interviews). On the other hand, recently a Thyssenkrupp alkaline electrolyser was approved for primary frequency control (interviews), while also flexibility can be added in the form of short-term battery storage, which can be integrated, an example of this system is referred to as a battolyser (Battolyser, 2020). This further shows that the advantage to handle flexible loads in some cases would allow for compromising on higher investment cost, or lower efficiency. The load flexibilities presented in Table 1 not to be assumed definite numbers, since under-or-overload, dependent on the longevity, can also result in higher efficiency degradation. Integrated systems are currently in a demonstration phase and therefore actual results are scarce and generally unknown.

For flexibility, also the hot idle and cold start ramp up times of electrolyser systems play a role. Shortly put, this is the time it takes for the system to start up, from standby or "hot" and from start or "cold". PEMEL again gains an advantage, this time because of having lower cold and hot idle ramp-up times, shown in Table 1. This can be of importance especially where a fast response to the renewable energy source is required to capture curtailed energy. Nonetheless, this advantage can be limited, as getting a PEMEL system to the required pressure level also can take up to 5 minutes (interviews). Additionally, it can be argued that there simply is only a limited necessity of systems responding in seconds to wind or solar energy is, as energy from a wind turbine does not suddenly stop in seconds, and for solar, cloud formation is limited in many areas where PV farms are located.

3.6.3 System footprint

Thirdly, another important factor not incorporated in the costs is the footprint of the total system. Footprint of the system can be of importance, as there are applications for electrolyser systems where land is scarce or expensive and a smaller system is needed or moreover, when the system is fitted into containers for permitting or transport reasons. As shown in the graphs below, currently smaller PEMEL systems have a significant smaller footprint, although this advantage decreases in the future, as in the future Alkaline systems are expected to make improvements (Hydrogen Europe, 2020a), and this advantages is also reduced with larger system capacities, as shown by analysing Nel's PEMEL and AEL electrolysers (Bloomberg, 2019).

Cases where there is a need for systems with a smaller footprint are for instance a hydrogen refuelling station in an urban area or when considering a new concept, where an electrolyser is placed offshore directly connected in different ways to an offshore wind park, hereby using possible advantages with integration and lower energy transport costs. The latter currently being a hot topic in countries in Western Europe surrounding the North Sea, where offshore wind is seen as the main option for renewable electricity generation. In these integrated offshore systems electrolysers with different qualities are preferred, such as footprint and the previously mentioned, system flexibility, which can justify for higher costs.

3.6.4 Use of precious metals

Additionally, the use of precious metals in the stack and in the system can make system costs dependent on fluctuating prices of precious metals. The use of precious metals is, as shown by the fin table 1, mainly a problem for PEMEL. For AEL and AEMEL this problem is non-pertinent and even more so for SOEL, where it is non-existent. PEMEL mostly requires iridium and platinum in stack, whereas in the complete system, excluded in table 1, it also requires titanium. AEL does require ruthenium, but also steel and nickel in the complete system.

Nonetheless, for PEMEL systems there is a lot of R&D going into the search for new inexpensive stack materials, and retrieving and recycling precious metals used, to solve this issue, but this remains an uncertain factor. Overall, for all technologies, decrease in material use is seen as a main contributor to the predicted cost reductions.

3.7 Outdated sources

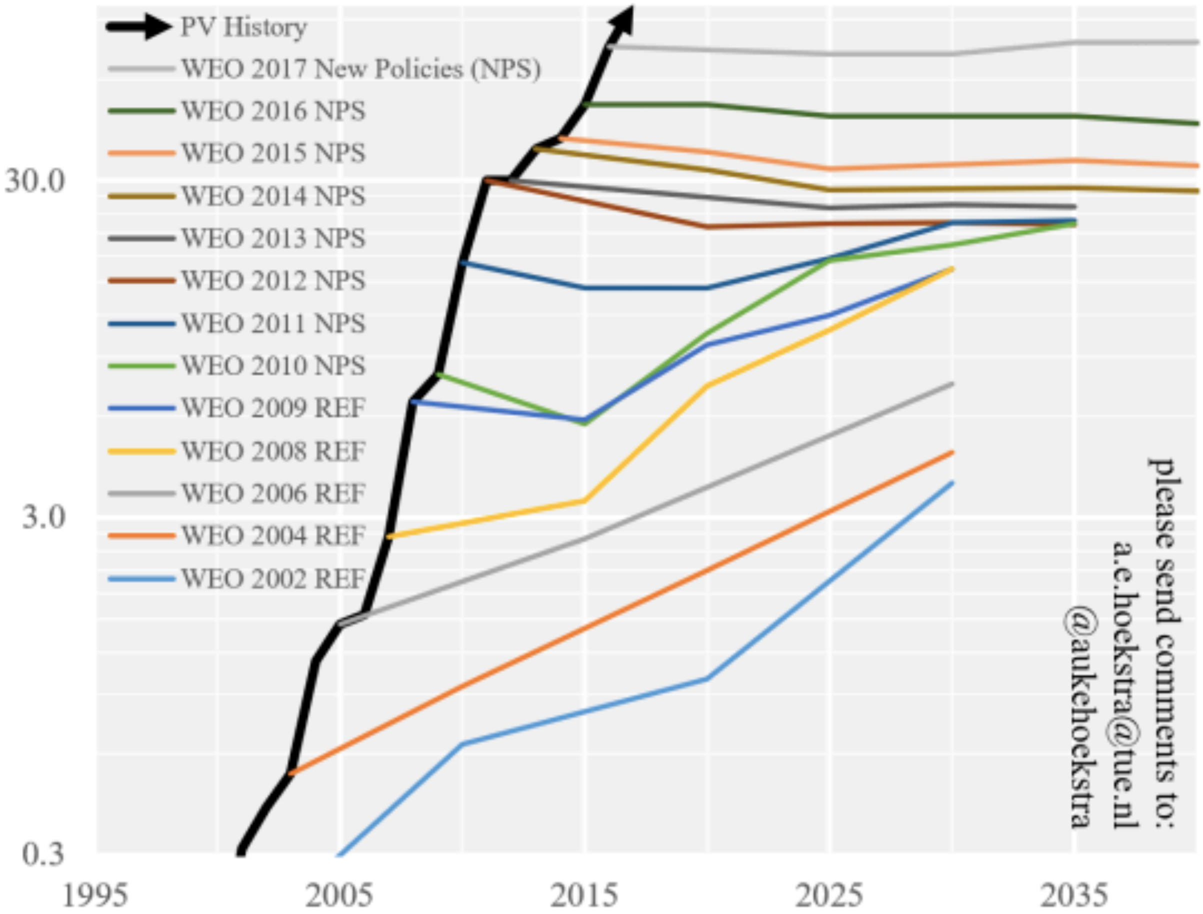
The third reason for the discrepancies in the data relate to the used sources for these continuously improving technologies. To exemplify this problem, this study looks into an often used and quoted study, the IEA's Future of Hydrogen. When comparing the Future of Hydrogen (IEA, 2019) to other recent studies by the Hydrogen council (2020) and the 2x40 GW initiative (Hydrogen Europe et al., 2020b), some of IEA's estimates seem conservative. In terms of cost, the IEA seems to base their predictions around Schmidt et al. (2017), which when looking at other studies into projected cost reductions is a commonly used source. However, the data gathered in this study is collected in 2016 which arguably is, for a continuously improving technology, already outdated. Moreover, the estimates from Schmidt et al. (2017) come from a small expert panel of mostly academic experts and their expert knowledge is in most cases not based on actual production cost data from a company, but rather from other studies and cost data elsewhere available, which in most cases would originate from before 2016. This would mean most knowledge and related data points originate back to studies and their predictions from before 2016. This example shows an underlying problem in an energy analysis, not just relating to green hydrogen, while more specifically relating to the IEA. In the next section, this underlying problem is amplified, when considering the speed and timing of the adoption of renewable technologies.

3.8 Speed and timing of adoption

This final reason for the discrepancies in cost predictions originates from discrepancies in the speed and timing of the adoption of green hydrogen. Visible when analysing Figure 5: Investment costs for green hydrogen production technologies, as it does show some level on agreement that the investment costs will reduce to certain level. All but one datapoint in 2050 is below 1.5 million, and it can therefore be concluded that the divergence is largest in terms of speed, timing and the current cost in 2020. Reports understating the speed and timing of adoption, also underestimate future deployment levels, and below, reports from the IEA are used as an example to illustrate this problem. A reason for this conservatism originates from the discussion is the time it takes to adopt renewable energy and its technologies. This can also be seen as a one of “chicken and egg” problems facing renewable energy technologies, such as green hydrogen. An issue which is also visible for the transmission of renewable energy, whilst even more clearly on the infrastructure side of battery and fuel cell vehicles: no infrastructure is built when there is no demand for it, while no BEV’s or FCEV’s will sell when there is no infrastructure to support it. When relating such an “chicken and egg” problem to cost reductions and increased deployment, it translates in investors holding back investments to wait for future cost reductions, while cost reductions depend on scale and learning effects and thus increased deployment, which will not come with time but with deployment.

Once again the problem clearly shown in reports from the IEA on renewable technologies, this time the IEA underestimates speed and timing of adoption, adding to the problem of the IEA studies mentioned in section 3.7. This exemplifies the larger underlying problem of the IEA underestimating renewables. This is typically illustrated in the figure below, which shows the actual annual additions in PV capacity versus the additions the IEA predicted in their yearly New Energy outlook on a log scale, showing IEA predicting linear growth while the actual growth is exponential.

Figure 7: Actual annual PV capacity addictions vs. IEA's New Energy Outlook (Installed capacity in GW, log scale)



Source: Hoekstra (2018)

This ongoing understating of the deployment of renewables, together with recycling data, showed in the example from section 3.7 can be seen as main reasons for the conservatism of the IEA. Subsequently, since the IEA is a commonly used source and its estimates regularly provide data input for other studies, consequences be substantial. Carrington and Stephenson (2017) conclude that the conservativism of the influential IEA hampers growth of renewables, in their study also using solar PV projections as an example. They argue that conservative projections deter investors and therefore can lead to delayed adoption of renewable energy technologies. This stresses the importance of accurately projecting the potential of renewable energy technologies, especially in well-read reports. Additionally, it reveals the complicated task of predicting speed and timing of adoption with scenario analyses, or in other words, projecting cumulative capacity on specific time periods.

However, in learning curve theory speed and timing of adoption do not affect costs directly, rather indirectly through increased deployment. Consequently, the solution for this problem presents itself in the learning curve theory, where time is an independent variable and thus, the speed and time of adoption do not play a role in deriving learning rate. Referring back to the quote from MacDonald & Schrattenholzer (2001) on page 9: " *For most products and services, it is not the passage of time that leads to cost reductions, but the accumulation of experience".* Hence, when deriving a learning rate there does not necessarily exist a need for assessing the speed and timing of the adoption of green hydrogen and its technologies. Still, issues on system boundaries, looking beyond investment costs and outdated data, remain when deriving learning rates, adding to the already mentioned empirical issues in section 2.4.

3.9 Solutions

3.9.1 Expert elicitation

Deriving learning rates already was presented as an adequate assessment to study the potential of green hydrogen in. However, deriving unbiased and significant learning rates require an extensive data set, which also results from the empirical issues summarized in section 2.4. However, installed capacity for green hydrogen is currently at low levels and a market for green hydrogen has not yet emerged (Hydrogen Europe, 2020a), providing for a limited dataset to begin with. Furthermore, similar to Ferioli et al. (2012) deriving learning rates for the ammonia production, green hydrogen, although to a lesser extent, is dependent on feedstock costs. Thus, the significant effect of efficiency and efficiency degradation need to be acknowledged when deriving the learning rates. Otherwise, when not incorporating possible improvements in efficiency, derived learning rates can become negatively biased, or even insignificant, such as in the ammonia production (Ferioli et al., 2012). Including both variables once more adds to the comprehensiveness of the dataset needed, with data which already is limitedly available. Proxies can be used such as PEM fuel cells, the reverse process of PEMEL, or the Chlorine Alkali process, which is similar to AEL. However, the proxies were seen as too different with all other important KPI's previously mentioned, basing the cost development or learning rates on proxies would not provide for a valuable analysis. Hence, another method to replicate a structured and comprehensive data set is proposed, namely an expert elicitation, which additionally addresses the remaining problems related to the disparity in the data.

In an expert elicitation, a panel of experts is consulted to predict values for different uncertain parameters. Morgen (2014) describe the relevance of expert elicitations as follows: "*Society often calls on experts for advice that requires judgments that go beyond well-established knowledge*". Next to this, expert elicitation is known as good practice in situations where structured and relevant data is only limitedly available (Meyer & Booker, 2001). In energy analysis it is commonly used, for instance by the US Department of Energy (the National academics, 2007) and for wind energy by Wiser et al. (2016) (Baker et al., 2015). The previously mentioned study Schmidt et. al (2017) similarly used expert elicitation to assess future potential of water electrolysis, and this study subsequently served as the basis for, among many other studies, predictions by the IEA (2019), adding to the significance of the expert elicitation method. In this way, expert elicitation is in fact a data collection method, hereby creating the possibility to accurately define system boundaries similar to all experts and thus, solving the problem of comparing systems with different systems, presented in 3.5. Next to this, experts can be requested to elicit values for scenario's not relating to specific time periods, yet directly relating to levels of deployment or cumulative capacity. Moreover, to solve the problem presented in section 3.6 on the importance looking beyond investment costs, other uncertain parameters next to investment costs, can be elicited from the panel of experts. Yet, the challenge remains to integrate the factors influencing the performance of water electrolysis beyond investment costs, summarized in section 3.6, in the learning rate. As already proposed by the Joint Research Centre (2012), one way of tackling this is to derive the all-encompassing levelized cost of, in this case, hydrogen (LCOH).

3.9.2 Levelized cost of hydrogen

In energy analysis, calculating levelized costs is a common way of analysing production cost. Thereby, total costs over lifetime are transformed to cost per unit of energy, which in the case of hydrogen usually presented per kilogram or kilowatt-hour. In this way, using levelized cost to derive learning curves, important end-use cost drivers excluded in investment costs can be incorporated.

To derive the total cost over lifetime and also, to the produced hydrogen over lifetime to in turn come to the cost per unit of energy feedstock input costs is needed, which is a variable normally considered as exogenous (Söderholm & Sundqvist, 2007). Feedstocks for hydrogen production include water and electricity and especially electricity input costs and capacity, normally referred to as load factor, for a large part determine the levelized cost of hydrogen (Bloomberg, Hydrogen Council, Hydrogen Europe 2020a+b). Normally feedstock costs is seen as an exogenous variable, however, endogenous variables Efficiency and efficiency degradation partly determine the hydrogen produced and thus the electricity input needed. Moreover, System flexibility, System **footprint** and **Fout! Verwijzingsbron niet gevonden.** simultaneously determine the electricity input and price. As systems more flexible in load range, with a smaller footprint or with faster ramp up times, can profit from more input capacity or from running when electricity prices from RES are at low or even negative levels, for instance during peaks, also explained in section 3.3.. Therefore, this study concludes that, for green hydrogen production, feedstock input capacity and price need to be seen as variables which are partly endogenously determined and hence, cannot be assumed exogenous and subsequently need to be controlled for when deriving green hydrogen costs and learning curves. Therefore, in this study, electricity costs and load factor are differentiated to come to a learning rate per case of assumed electricity costs and input. This leads to multiple variating learning rates, making the results and implications harder to comprehend. Therefore, results on the LCOH and learning are applied to specific cases, which are also especially applicable the port of Rotterdam. Hereby, learning curve theory remains of key importance, as the argued potential cost reductions still result from increased deployment. This results in the following hypothesis, which lays the foundation of how the results are presented in this report:

It is of key importance to look further than learning rates based solely on investment costs, as other endogenous and exogenous factors have a significant impact on the actual costs of green hydrogen.

This hypothesis is tested in this study:

1) By developing variable learning rates based on the levelized cost, which leads to a more complete picture by showing differences in the ability to learn depending on electricity costs and load factor.

2) By applying the variable learning rates in both grid-and off-grid cases, showing the effect of other KPI's endogenously affecting electricity costs and load factor, and the potential of integration with renewable energy sources and, of possibly importing green hydrogen from locations with high renewable potential.

4. **Methodology**

4.2 Levelized cost of green hydrogen

In equation 2 for the levelized cost of hydrogen, electricity costs are explicitly separated to enable differentiating between electricity costs and the other cost variables. Additionally, stack replacement costs are incorporated, as generally stacks are replaced to limit cumulative efficiency degradation, which would drive up electricity costs. System flexibility, System footprint and ramp-up times influence the learning rate through load factor and electricity. Therefore, by differentiating electricity costs and load factor their influence can be assessed on a lower level.

Equation 2: Levelized cost of hydrogen (LCOH)

$$Levelized\ cost\ of\ hydrogen\ (LCOH) = \frac{Cost\ over\ lifetime}{Hydrogen\ produced\ over\ lifetime} =$$

$$= \frac{\sum_{t=1}^{n} \frac{(I_t + W_t + M_t + R_t)}{(1+r)^t}}{\sum_{t=1}^{n} \frac{U_t \times \eta_t}{(1+r)^t}} + \frac{\sum_{t=1}^{n} \frac{U_t \times LCOE_t \times (1+d^t)}{(1+r)^t}}{\sum_{t=1}^{n} \frac{U_t \times \eta_t}{(1+r)^t}}$$

$With$:

I_t $= Capital\ Expenditures\ of\ the\ complete\ system\ in\ €/kW_{input}\ , in\ year\ t$

W_t $= Water\ costs\ in\ €/kW_{input}\ , in\ year\ t$

O_t $= Operations\ and\ Maintanaince\ costs\ €/kW_{input}\ , in\ year\ t$

R_t $= Stack\ replacement\ costs\ in\ €/kW_{input}\ , in\ year\ t$

η_t $= Efficiency\ of\ the\ complete\ system\ in\ \%, in\ year\ t$

U_t $= Utlization\ in\ load\ hours\ per\ year, in\ year\ t$

$LCOE_t$ $= Levelized\ cost\ of\ electricity\ in\ €/kWh\ , in\ year\ t$

n $= Lifetime\ of\ the\ complete\ system, in\ years$

r $= Discount\ rate\ or\ WACC, in\ \%$

d^t $= cumulative\ efficiency\ degradation, in\ year\ t$

$$= (U_{t-1} \times\ years\ after\ stack\ replacement$$
$$- 1\ \times degradation\ rate\ per\ hour)$$

The following assumptions are made, based on Bloomberg (2019), Hydrogen Europe (2020 and company (brochures), and subsequently reviewed by experts:

- Economic lifetime is assumed at 30 years, with sensitivity analyses for 20 and 40 years.
- Discount rate or weighted average cost of capital (WACC), is assumed at 6.5%, with sensitivity analysis for 3 and 10%.
- Installation costs are considered to be 10% of CAPEX or I_t, however, as this is highly dependent on location, different per manufacturer and lower for containerized systems, sensitivity analysis is done for 0 and 20%.
- Operations and Maintenance or O_t , is assumed at 2% of yearly CAPEX, sensitivity analyses are performed for 1 and 3%, as it is dependent on the service level agreement (SLA).
- Cost of water (W_t), are neglectable, with water costs at €0.00036 per litre and usage at <0.09 litre per kg of hydrogen (Thyssenkrupp, 2020a).
- Stacks are replaced every 10 years (AEL and PEMEL), and both stack costs[6] and efficiency degradation of newly placed stacks are assumed to improve with increased deployment and time. Stack efficiency degradation is assumed to fall from 0.11%/1000 hrs for AEL and 0.19% for PEMEL before the first stack replacement to a constant 0.1%/1000hrs for both, after the stack replacements at year 10 and 20 (Hydrogen Europe, 2020a). With increased deployment levels, efficiency degradation is assumed constant at 0.1%/1000hrs

Following the assumptions, the three key remaining uncertain parameters are:

- Capital expenditures
- Stack replacement costs
- Efficiency

Additionally, another usually studied uncertain parameter, lifetime of the stack in hours, is elicited from the experts, as most studies address efficiency degradation in the form of lifetime of the stack. Since efficiency degradation was seen as confidential information, this study assumes current levels degradation as presented by Hydrogen Europe (2020a). The elicited variable lifetime in fact represents economic lifetime, as it shows the cost-optimal time to replace the stack after efficiency has degraded to a certain level. Therefore, lifetime is also dependent on electricity costs and load factor, as those variables impact the economic

[6] Improvements in stack replacement costs come with deployment and in this study, it is assumed that stack replacement costs after 10 years come to the values of the 10x times deployment scenario explained further in subsection 4.3.1

incentive to replace stacks. However, this study focuses on the relative improvements in lifetime, which can only result from improvements in stack degradation. These relative percental improvements in lifetime are then transformed to improvements in stack degradation, and then compared with the predicted values from Hydrogen Europe (2020a). Current degradation levels are taken from Table 1 (Hydrogen Europe, 2020a).

4.3 Expert elicitation

The study by Schmidt et al. (2017) is used as a foundation for expert elicitation conducted in this study, but it differs with on a couple key points. Firstly, the values from experts are not elicited during the interview and instead are elicited beforehand in an online survey and afterwards, discussed in an interview, together with the insights and elicited values from other experts, where the expert also has the possibility to change his elicited values. This creates an interactive, iterative aspect, which can be seen as a scoped version of the Delphi method[7]. Secondly, this study focuses its attention to experts from within the industry, instead of mostly using academic experts, as industry experts get closer to the actual production and the actual cost data. Academic experts are contacted in a similar matter and both their insights and estimates in the survey are used, however, exclusively in a controlling function. Thirdly, the scenarios, for which experts are asked to predict values, are not based around time periods. As has been argued before in section 3.8, this eliminates the uncertainty about the timing and speed of adoption, which are independent variables in the learning rate. The scenarios used instead represent different levels of deployment, scale and R&D expenditures.

4.3.1 Survey

The uncertain factors influencing the cost of green hydrogen are the capital costs and the total electrical efficiency of the complete system, the lifetime and replacement cost of the stack. For both the CAPEX as well as the efficiency, it was emphasized to the experts in the survey that it concerned the complete system needing only non-purified water and AC electricity as input, to prevent for the problem of different definition of system boundaries. To reduce overconfidence and allow for uncertainty, values were elicited in ranges. Slider bars were used in the survey to limit the perceived sensitive data requests and increase time efficiency for the experts. Also, the experts were triggered by setting the standard range

[7] In the Delphi method, in multiple rounds questionnaires are sent out to an expert panel and after each round findings are discussed with the expert panel, creating an structured interactive discussion

values based on IEA's Future of Hydrogen (2019), also quoting IEA's estimates in the question to provide for a base value, probing the experts to cogitate. For all parameters first a current benchmark value was requested, based on a system with a 20 MW total stack. Hereafter, per parameter for different scenarios estimated ranges were elicited, with experts always being able to see their benchmark values. Afterwards, the experts were asked to argue their values with underlying reasons, and to specifically point the arguments to the scenarios. The scenarios in the survey are based around learning curve theory, while more specifically acknowledging the difference scale, R&D and deployment effects have on the uncertain parameters. For the learning curve theory to apply the survey lets experts think what effect a doubling of deployment would have in for the different parameters. However, the difference with larger scale stacks, which have a different cost reductions mechanism – economies of scale, needs to be stressed. Therefore, to control for experts overestimating deployment by mixing in scale it was stressed the scenarios all related to a 20MW system, besides the scenarios depicting different scales of course. Scenarios for R&D expenditure were included to enable comparisons between the effect of policy measures focusing on R&D or on deployment, hereby not serving the purpose of deriving a learning-by-searching rate.

4.3.2 Interviews

After conducting the survey, experts were asked if they would be willing to discuss results and share insights. Hereby, experts were allowed to change elicited values. The interviews were used interactively by noting opinions and insights of other experts to the expert to initiate a discussion. The interviews followed the following steps:

1. Check for unanswered questions
2. Check for possible outliers filled in by the expert and try to find its reasoning
3. Discussion of elicited values vs general averages
4. Discussion on system integration and system boundaries
5. (Dis)advantages AEL vs PEMEL and to a lesser extent SOEL and AEMEL
6. End-use sectors and renewable integration
7. Recent developments and proposed policy advices

4.4 Fixed effects

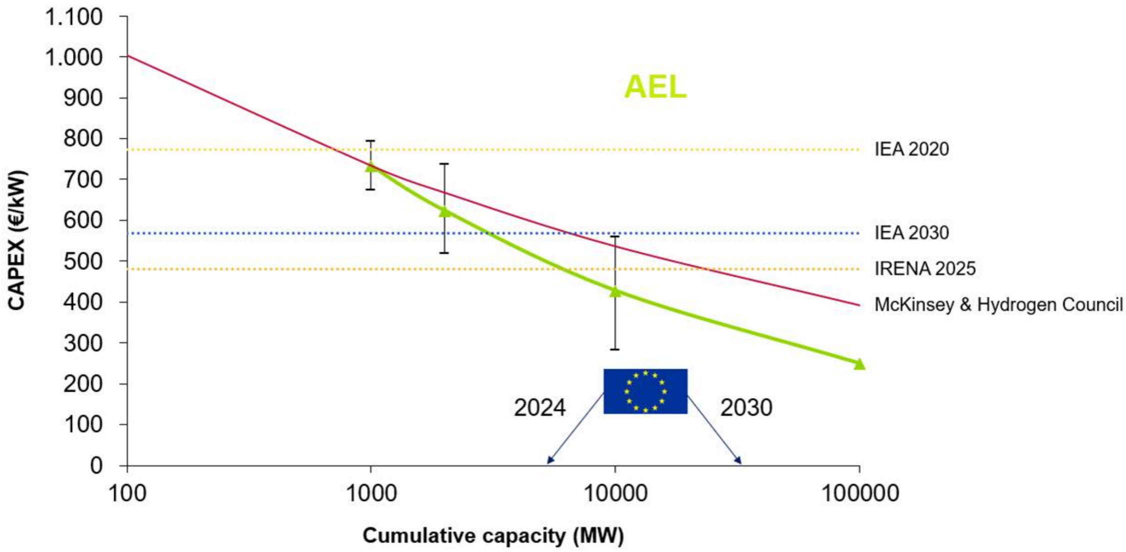
The data from the expert elicitation is used levelized costs for hydrogen are derived per expert and per scenario. The resulting differences per industry expert were subsequently averaged out to come to the learning rates. This is similar to the fixed effects model, a statistical model commonly used with panel data which excludes time invariant variables and hereby controls for omitted variable bias (Wooldridge, 2016). In this case, it controls for variables included by experts, which are invariant to the different scenarios.

5. Findings

5.2 Comparison of CAPEX

In this section, the results on CAPEX for Alkaline are compared to current literature and visualised below, whereafter the presented data again is used to touch upon the underestimation of renewables by the IEA. This is done shortly, as mentioned before, it is very important to go further than CAPEX.

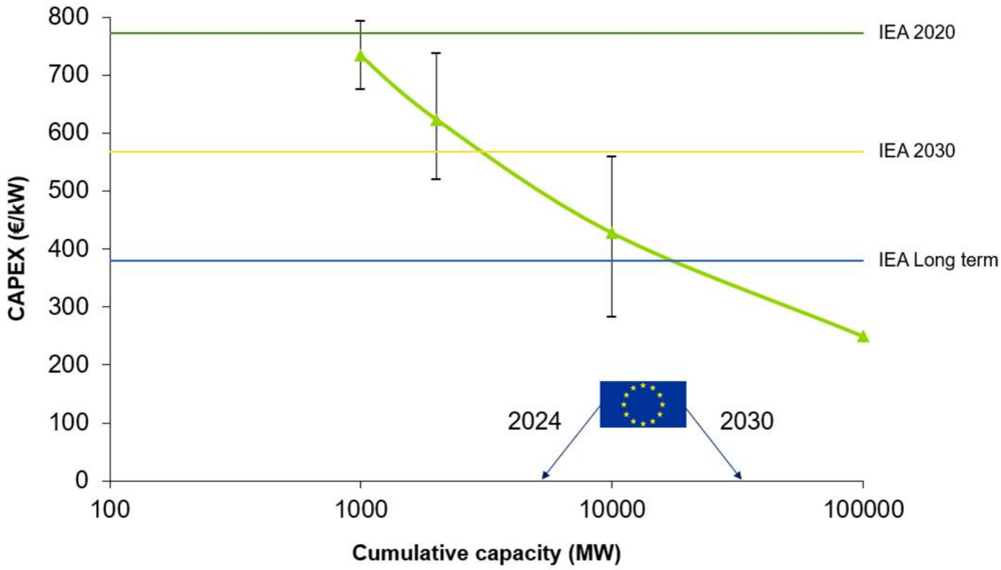
Figure 8: Alkaline CAPEX learning curve vs current literature



The figure above shows the learning curve for investment costs, based on capacities mentioned in the EC hydrogen strategy (2020). Here current cumulative capacity of 1000 MW for Alkaline is based on chlor alkali and additionally the assumption needs to be made that all of the installed capacity will be AEL and is in the EU, which are not optimal. However, this is needs to be seen as purely illustrative, enabling the introduction of the EC targets and comparison with other studies, and also; these are not the main results of this study. What figure 7 shows is that, besides compared to IRENA, this study estimates lower CAPEX levels are reached sooner than predicted. Also showing a steeper learning curve than the Hydrogen council (2020) with a learning rate for AEL[8] of 16 ± 8%, compared the 9% from the Hydrogen council.

[8] All learning rates are based on the 10x times deployment scenarios, since it showed significantly lower uncertainty levels than the 2x times deployment scenarios, in all cases.

Figure 9: IEA underestimating renewables: also the case for green hydrogen



Zooming in on the IEA (2019) in the figure above, it results in the confirmation that the IEA also underestimates the performance of Alkalinewater electrolysis. IEA's CAPEX predictions for Alkaline in 2030 are to be reached even before 2024, or with first doubling of cumulative capacity. Moreover, IEA's long-term targets, presumably around 2050, are even reached before 2030. The underlying reasons are already discussed in section 3.7 and 3.8, where also potential harming consequence is mentioned; investors being deterred by the underestimation the influential IEA which can hamper the growth.

This also confirms the giant leaps in technological progress Alkaline electrolysers have already made in recent years, also confirmed in the interviews, resulting from among others increases in current density. This fast pace of progress makes older literature outdated, especially when this is literature summarizing or using data from again older literature. The future projected cost reductions are mainly the result of the industrialization in the manufacturing of stacks, with (semi)automation in production lines, but also increasing purchasing power for raw materials needed, but also for additional parts needed for the balance of plant (BoP). The industrialization of AELs is confirmed by the recently announced substantial increases in electrolyser production capacities by Nel and ThyssenKrupp.

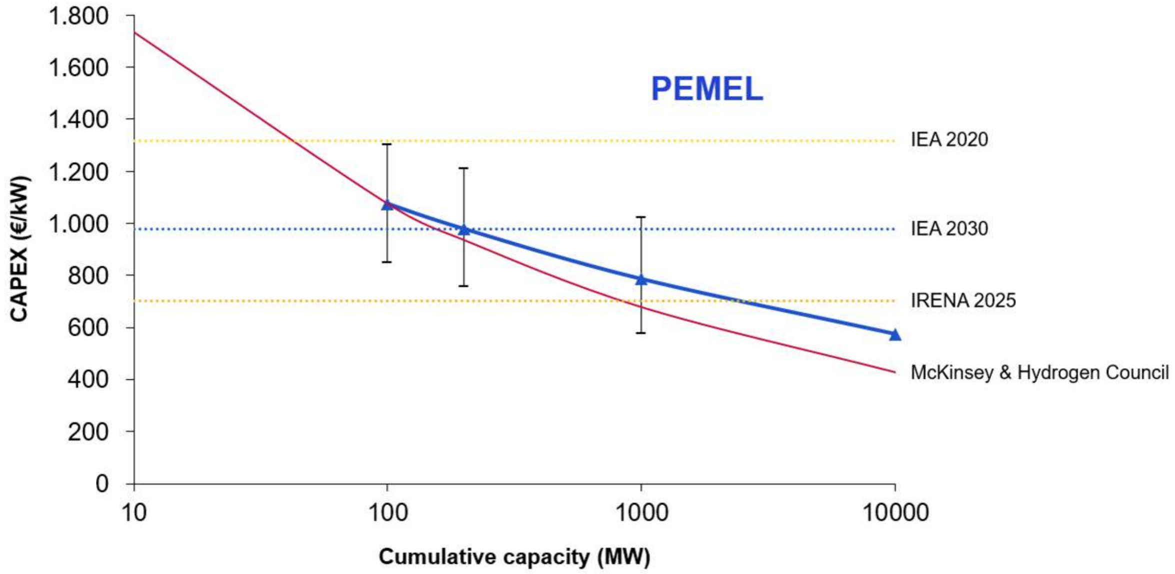
Table 2: Announced capacity expansions for electrolyser production [9]

Company	Sort	Capacity and year
Nel	AEL	360 MW/a, further expansion to >1000 MW/a possible (*Graré, 2020)*
ThyssenKrupp	AEL	1,000 MW/a *(Thyssenkrupp, 2020b)*

[9] Production capacity before these expansions for all OEMs were only several MWs per year (interviews).

ITM power	PEMEL	1,000 MW/a *(ITM, 2019)*
Enapter	AEM	240 MW/a by 2022 (*Enapter, 2020)*

Figure 10: PEMEL CAPEX learning curve vs current literature



The main takeaway from figure 9, PEMEL's investment costs learning curve, is that the predictions from current literature are more in line, while the Hydrogen council (2020) predicts a higher learning rate. This is underlined by insights gathered in the interviews, where experts stated the substantial technological progress of incumbent AEL in recent years, whereas the newer PEMEL never realised the expectations in terms of costs, due its high use of precious metals. This is also reflected in the learning rate 9 ± 2%, versus the 13% by the hydrogen council (2020). This is also an example of the problem mentioned in section 3.7, of recycling outdated sources, which in this case it has led to a bias in literature where PEMEL is regarded as the main technology for the future of water electrolysis, also having a steeping learning curve, overlooking recent progress from AEL. Again, it should be noted that it important to look further than CAPEX. Mainly the flexibility, system size and integration options are fields where PEMEL is presumed to excel over AEL, although this has yet to be proven. Additionally, out of the interviews came that AEMEL, without the need for precious metals already provides an alternative to PEMEL, although learning rates are impossible to establish for this new technology[10].The capacity expansion from Enapter, shown in Table 2 shows its potential. However, this section does not want to indicate that only one single technology will exist in the further future. On the contrary, this paper has shown the variety of applications for water

[10] Enapter, the company which holds the patent on AEM electrolysers, only exists for 3 years.

electrolysis, while the differences between the technologies show that while one technology may be more suited in one end-use sector, another is better suited in another. This is confirmed by all technologies expanding capacity, in Table 2.

5.3 Variable learning rates

5.3.1 AEL

Referring to the first goal (0, the variable learning rates for AEL for the levelized costs are shown in table 2 below, based on levelized costs of hydrogen, and depending on electricity price on the vertical axis and load factor on the horizontal axis. Based on investment costs only, the learning rate for AEL[11] is 16 ± 8%.

LCOE (€/MWh)

50	9%	7%	5%	4%	4%	3%	3%	3%	3%
45	10%	7%	6%	5%	4%	4%	3%	3%	3%
40	10%	7%	6%	5%	4%	4%	3%	3%	3%
35	10%	8%	6%	5%	5%	4%	4%	3%	3%
30	11%	9%	7%	6%	5%	5%	4%	4%	4%
25	12%	9%	8%	7%	6%	5%	5%	4%	4%
20	12%	10%	8%	7%	7%	6%	5%	5%	5%
15	13%	11%	10%	8%	8%	7%	6%	6%	6%
10	14%	12%	11%	10%	9%	8%	8%	7%	7%
5	15%	14%	13%	12%	12%	11%	10%	10%	10%
0	16%	16%	16%	16%	16%	16%	16%	16%	16%
	1000	*2000*	*3000*	*4000*	*5000*	*6000*	*7000*	*8000*	*8760*

Table 3: Variable learning rates AEL

Load factor (hours/year)

The variable learning rates in table 2 show that with differing electricity cost and load factor, the learning rates differs significantly as well, ranging from 3 to 16%. Compared to the investment cost learning rate of 16 ± 8%, the levelized costs of hydrogen show a lower overall potential to learn, and with increasing load factor and energy costs, the ability to learn decreases even further to a minimal learning rate of 3%. This is illustrated by the fact that 70-90% of total costs are electricity costs in cases with learning rates below 7%, in the upper right cases in table 2. This shows that in these cases, green hydrogen costs are more dependent electricity costs and hence, on the learning rate of the renewable energy source. This leads to the conclusion that the variable learning rates shown are dependent on

[11] All learning rates are based on the 10x times deployment scenarios, since it showed significantly lower uncertainty levels than the 2x times deployment scenarios, in all cases.

electricity costs and load factor to transform into single constant learning, rate for the learning curve theory to apply to the LCOH.

5.3.2 PEMEL

For PEMEL the learning rates based on investment costs is 9 ± 2% and the variable learning rates table looks as follows:

Table 4: Variable learning rates for PEMEL

LCOE (€/MWh)

50	7%	6%	5%	4%	4%	4%	4%	3%	3%
45	7%	6%	5%	5%	4%	4%	4%	4%	4%
40	8%	6%	5%	5%	5%	4%	4%	4%	4%
35	8%	7%	6%	5%	5%	4%	4%	4%	4%
30	8%	7%	6%	6%	5%	5%	4%	4%	4%
25	8%	7%	6%	6%	5%	5%	5%	5%	4%
20	9%	8%	7%	6%	6%	6%	5%	5%	5%
15	9%	8%	7%	7%	6%	6%	6%	6%	5%
10	9%	9%	8%	8%	7%	7%	7%	6%	6%
5	9%	9%	9%	9%	8%	8%	8%	8%	7%
0	10%	10%	10%	10%	10%	10%	10%	10%	10%
	1000	*2000*	*3000*	*4000*	*5000*	*6000*	*7000*	*8000*	*8760*

Load factor (hours/year)

In table 4 for PEMEL, similarly as for AEL, it shows the dependence of the learning rate on electricity costs and load factor, although for PEMEL, the divergence across the variable learning rates is lower. This originates from efficiency improvements for PEMEL, which showed a higher ability to learn, and on the other hand, from the lower reductions in investment costs, which showed a lower ability to learn. The latter also shows in the significantly lower learning rate on investment costs of 9 ± 2%. The higher use of precious metals of PEMEL can be seen is one of the main reasons, which is reflected in the learning rate of the investment costs, whilst also in the limited reductions possible in the stack replacement cost, both making the part of technology which can learn lower. Although, when a new inexpensive stack material is discovered, this would result in a shock off shifting the learning curve downwards, however this could also be seen as a new technology. Next to this, overall lower efficiencies of PEMEL result in a lower total amount of hydrogen produced with the same electricity input, increasing electricity costs. Improvements in efficiency with increased deployment increase the variable learning rate relatively more in cases with higher load hours and electricity costs, where logically, improvements in efficiency have more impact on the LCOH.

However, the advantages of PEMEL of more load flexibility, lower ramp-up times and lower footprint, presented in by KPI's summarized in Table 1: KPI's green hydrogen technologies, are overlooked. These advantages can lead to PEMEL capturing more load hours at lower prices, shifting the variable learning rate to higher levels - in table 4 diagonally to the bottom right. Experts argued the necessity for ramp-up times in seconds are a necessity and if it would actually lead to capturing significantly more low-priced energy, hereby also noting that flexibility of PEMEL in terms of load was not proven on a larger scale. Next to this, it was shown in subsection 3.6.3 that with increasing system size, systems footprints of PEMEL and AEL converge. Also, for AEL, adding short-term battery storage would result in extra load flexibility, although the same time, this would result in higher CAPEX and lower overall efficiency. The load flexibility or the battery storage needed in MWh's depends on the power fluctuations of the renewable energy source. This makes exact quantifications of these advantages difficult, differing per case with the power fluctuations of the renewable energy source, although in section 5.3 an illustrative example is presented.

5.3.3 SOEL and AEMEL

Regarding the two technologies with a lower technology readiness level (TRL), AEMEL and SOEL, SOEL in both the survey and interviews, showed to be more market ready than previously assumed. Therefore, quantitative estimates are made only for SOEL, while for AEMEL the future is more uncertain, although it is already currently used in remote areas in on small capacity scales. For SOEL the learning rate based on investment cost only is estimated at 27%[12]. A high rate, since SOEL investment costs are assumed to reduce significantly. For the variable learning rates for SOEL, 8000 load hours is assumed, resulting from the longer ramp-up times and for the foreseen applications for SOEL, which include for instance e-fuels production and steel production. Since the resulted stack lifetimes for SOEL were low, in this case stacks were replaced at year 5, 12 and 20, costing respectively 200, 130 and 80 €/kWh, and hereby, stack efficiency degradation at the start of production was assumed at 1.9% and become 1.0%, 0.7% and 0.5%/1000 hrs after each respective stack replacement (Hydrogen Europe, 2020a). Again, it should be noted that here, it is assumed that steam is available and hence, that electricity needed steam generation is not included in the costs. This leads to variable learning rate ranging from 12% to 28%, for the electricity prices 0-50€/MWh.

[12] There is no uncertainty boundaries, since only values from one industry expert were elicited.

The learning rate for a grid connected system for SOEL is significantly higher than the learning rates of AEL and PEMEL, which can be explained by the high efficiency of SOEL, whilst also by the fact that SOEL does not need precious metals in the stack. Higher efficiency leads to a lower dependence on electricity costs, since a larger part of the costs is determined by the more endogenous cost drivers, as more hydrogen is produced with the same input of electricity thus total costs of electricity can be distributed over more kilograms of hydrogen in the LCOH. Illustrated for SOEL by the fact that only 71-83% of the costs come from electricity, lower than the 76-87% from AEL. By not requiring precious metals in the stack, a larger part of the investment costs can learn, also shown by the high investment cost learning rate and reflected in the substantially decreasing stack replacement costs. This high learning rate remains constrained by the fact that with lower investment costs, dependency on electricity costs increases and hence, the variable learning rate will decrease and learning rate for SOEL too will become dependent on the learning rate of the renewable energy source.

To conclude, SOEL shows its potential to produce low-cost hydrogen where steam is available, next to this, SOEL technology can be used to produce electro-fuels in co-electrolysis with CO_2, for instance for the aviation or shipping sector. Although, it should be noted that longer stack lifetimes and thus, lower material degradation with the high temperatures, are yet to be demonstrated.

5.4 Cases

Referring back to second goal (2), based on the results from the previous section grid-and off-grid cases are used to illustrate the potential of green hydrogen, also in the port of Rotterdam. Interviews with experts and recent announcements from the port of Rotterdam, Amsterdam and Groningen lead to the following three most relevant cases, regarding the production of green hydrogen:

1. Grid-connected
2. Off-grid with possible integration
3. Large-scale production and the possibility of imports

5.4.1 Grid-connected

In grid-connected cases, load hours are assumed at 8000[13] hours per year, and in these cases a Power Purchase Agreement (PPA) is agreed with a renewable energy provider. Price in this

[13] Maintenance and operations, stack replacements are among others, reasons for not reaching the full 8760 hrs

case are assumed using the predicted offshore wind prices in the Netherlands for 2023-2030, ranging from 25-50 €/MWh[14] (CE Delft, 2017). In table 6 below, besides the resulting learning rates, also the absolute values from the benchmark and the 10x times deployment scenario are shown. Again, it should be noted that for SOEL steam is assumed available on-site, thus not energy costs for steam generation are not included.

Table 5: Learning rates (LR) and LCOH in the grid-connected case

	AEL	PEMEL	SOEL
Learning Rate	3-4%	3-5%	12-15%
LCOH (grid current deployment)	1.84-3.05 €/kg	2.49-3.97 €/kg	2.27-3.83 €/kg
LCOH (grid 10x deployment)[15]	1.63 –2.78 €/kg	2.22-3.68 €/kg	1.25-2.52 €/kg

The learning rates for AEL and PEMEL show that for grid-connected cases, the ability to learn is little due to the dependence of the LCOH on electricity prices with the high assumed load factor. Thus, again in fact making the learning rate of renewable electricity production more important. SOEL, however, shows a significantly higher learning rate. This, as previously mentioned, is due to the high overall efficiency and because SOEL lacks the need for precious metals. The higher variable learning rate, however, remains constrained by an increasing dependence on electricity costs, and thus again by the learning rate of renewable energy.

In this case, therefore, the absolute values for LCOH provide for a more distinctive analysis. Here, the results show again the high potential of SOEL, with costs coming down as far as 1.25 €/kg, although where steam is not available, AEL remains the leading technology. The implications of these LCOH's will be discussed in the final chapter of this study.

5.4.2 Off-grid with possible integration

For off-grid cases, however, endogenous learning for electrolyser systems can also come in the form integration with the RES, load flexibility, and lower footprint or ramp up-times, which can lead to the system unlocking higher load factors at lower electricity prices. Therefore a different case is assumed, where at benchmark the electrolyser system has a load factor of 4,000 hours[6] of wind electricity per year at 40 €/MWh[16] , and in the 10x times deployment scenario the system also "learns" additionally to capture 1,000 hours[17], of otherwise curtailed

[14] Excluding additional grid costs, such as grid connection and balancing, but also taxes.
[15] For the 10x deployment scenario, efficiency degradation and stack replacements costs were adjusted according to survey results and Hydrogen Europe (2020a)
[16] Lower price estimate from PBL, 2019 for offshore wind energy, excluding grid connection costs.
[17] This means 25% extra wind energy captured, following from interviews where values ranged between 20-40%, in Bloomberg (2019) currently estimate 15% energy cost reduction for wind, 20% for PV in integrated systems

energy at a lower price of 15€/MWh[18]. This case is not applicable for SOEL, as it is technically impossible.

Table 6: Learning rates and LCOH in the off-grid case

	AEL	PEMEL
Learning Rate (off-grid 10x deployment)	5 ± 2%	5 ± 1%
Learning rate (off-grid flexible and 10x deployment)[19]	19 ± 4%	18 ± 2%
LCOH (off-grid current deployment)	2.77-2.86 €/kg	3.74-4.32 €/kg
LCOH (off-grid 10x deployment)	2.39-2.82 €/kg	3.22-3.59 €/kg
LCOH (off-grid flexible and 10x deployment)[20]	2.08-2.42 €/kg	2.75-3.04 €/kg

The substantially higher learning rate shows the significantly higher ability of off-grid green hydrogen production to endogenously learn and thereby, it shows the potential of integrated green hydrogen production complementing and integrating with renewable energy sources. This case is illustrative, since thoroughly quantifying this potential is difficult, as it is highly dependent on the power fluctuations of the RES. Moreover, with high level of integration system boundaries become less obvious - where does the wind turbine end, and the electrolyser start. Also, two important additional advantages of integration are not included. Firstly, grid connections are significantly, 10x-20x, more expensive than hydrogen pipelines (Vermeulen, 2017) (Hydrogen Europe et al.,2020) (Hygro, 2020) and secondly, certain parts of the system can be left out or replaced by cheaper alternatives, such as the rectifier (Hygro, 2020). Hence, by optimally integrating both systems, and combining grid and pipeline connections, costs can be brought down further (Hygro, 2020). These cost reductions can be seen as a typical result of a combination of learning-by-doing and learning-by-searching. Therefore, for further research this study proposes an extensive cost analysis into the different integration options with renewable energy power. An example of high-level integration is the recently announced Crosswind consortium, consisting of Shell and Eneco, which plans to integrate offshore wind, floating PV, batteries and green hydrogen in a "Super hybrid" (Shell, 2020). Here, 200MW of the 759MW produced electricity is allocated for the production of green hydrogen for one of Shell's refineries in the industrial complexes in the port of Rotterdam.

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[18] In other reports, this curtailed energy was assumed free, however, this report assumes a lower price, because with rising demand for curtailed energy, free energy becomes more unlikely.
[19] For the 10x deployment scenario, efficiency degradation and stack replacements costs were adjusted according to survey results and Hydrogen Europe (2020a)
[20] For the 10x deployment scenario, efficiency degradation and stack replacements costs were adjusted according to survey results and Hydrogen Europe (2020a)

5.4.3 Large scale production and the possibility of imports

The port of Rotterdam also envisions an import hub for large green hydrogen imports, this can be in the form of ammonia, liquefied hydrogen or methanol from countries with high potential of wind, solar or a combination of both. Recently, tenders of PV solar energy in the middle east showed electricity prices going even below 15 €/MWh, almost going down as far as 10 €/MWh (Bellini, 2020). Using the 1 GW scenario from the survey for AEL[21], the following table shows the LCOH for gigawatt scale hydrogen production in regions with a high potential of renewables:

Table 7: LCOH (€/kg) 1 GW scale

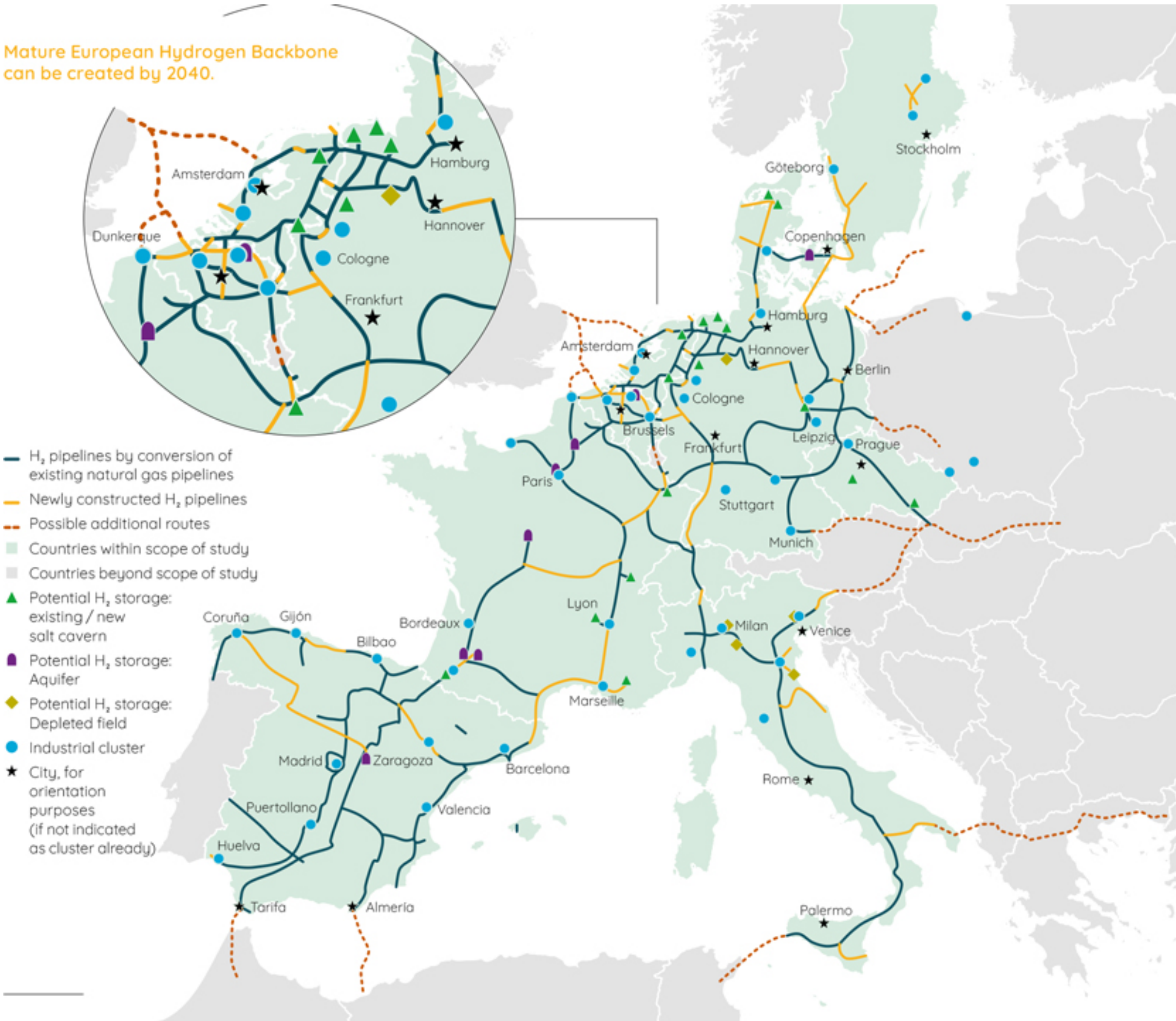
LCOE (€/MWh)	3000	4000	5000
20	1.51 €/kg	1.40 €/kg	1.34 €/kg
15	1.25 €/kg	1.14 €/kg	1.07 €/kg
10	0.98 €/kg	0.87 €/kg	0.81 €/kg
5	0.72 €/kg	0.61 €/kg	0.54 €/kg

Load factor (hours/year)

Table 7 shows that large scale production with low energy prices, already currently can lead to hydrogen prices going below 1€/kg. However, the costs of shipping hydrogen across continents, with for instance costs of liquefication or conversion to ammonia or methanol, and the subsequent reconversion, need to be addressed as well. The low current share of renewables in electricity production in the Netherlands additionally make imports an interesting alternative. Still, it is highly dependent on the costs of conversion and transportation and these gives ground for further research. Another option is shown by the European Hydrogen Backbone (2020), as the consortium of 11 European transmission system operators (TSO's) proposes to construct a hydrogen pipeline infrastructure across Europe by 2030, partly retrofitting existing gas grids, and even reaching to solar energy abundant North-Africa. This provides for a low-cost transport option, 0.09-0.17 €/kg/1000km (European Hydrogen Backbone, 2020), to unlock imports of green hydrogen produced by for instance Danish offshore wind, Southern European solar PV or PV/wind hybrids and even, by North-African solar PV.

Figure 11: Proposed European hydrogen backbone

[21] Only AEL is considered at which is currently the only technology feasible to produce at this scale and in the future it also remains economically the best option (interviews).



Mature European Hydrogen Backbone can be created by 2040.
Amsterdam
Hamburg
Hannover
Dunkerque
Cologne
Frankfurt
H₂ pipelines by conversion of existing natural gas pipelines
Newly constructed H₂ pipelines
Possible additional routes
Countries within scope of study
Countries beyond scope of study
Potential H₂ storage: existing / new salt cavern
Potential H₂ storage: Aquifer
Potential H₂ storage: Depleted field
Industrial cluster
City, for orientation purposes (if not indicated as cluster already)
Stockholm
Göteborg
Copenhagen
Berlin
Brussels
Leipzig
Prague
Paris
Stuttgart
Munich
Lyon
Bordeaux
Milan
Venice
Coruña
Gijón
Bilbao
Marseille
Madrid
Zaragoza
Barcelona
Puertollano
Valencia
Rome
Huelva
Tarifa
Almería
Palermo

6. Strategic Implications

6.2 Starting a hydrogen economy

The overall ambition to start a worldwide green hydrogen economy is underlined by the absolute values for the levelized costs of hydrogen, which are already at significantly lower levels than previously assumed, by for instance the IEA (2019), which predict LCOH of 2.5 €/kg for 2030 and 1.4-2.0 €/kg for 2050. In the 10x times deployment scenarios, which in Europe, according to EC targets should be reached well before 2030 (2020), costs are shown to decrease faster than the IEA expects, however, the results also show LCOH remain highly dependent on electricity price and load factor. More easily comparable are the CAPEX or the investment costs, which the IEA predicts at around 380 €/kW[22] fir AEL in the long term (beyond 2030), while this study and also industry experts predict these or even lower levels of CAPEX to be reached before 2025. This once again confirms the conservatism of the IEA, underestimating potential of renewable energy technologies. More extensive comparisons of CAPEX are found in the Appendix, however, as concluded before in this report, comparing solely CAPEX leads to biased conclusions, since other important KPI's are overlooked. Conclusively, the potential of the worldwide hydrogen economy for low-carbon hydrogen to kick-off is underlined by costs reductions of green hydrogen technologies, which outpaced predictions, where mainly the mature AEL and SOEL technologies exceeded expectations.

For what values the levelized cost will become competitive in the different sectors is something that requires further research, and here shortly touched upon. For the industry hydrogen is already used heavily in the fertilizer (ammonia) and chemical (methanol) sectors, while in the future high temperature industrial heat, which cannot be electrified in these sectors such as the steel sector, provides for future potential. Ammonia is already used heavily in the fertilizer industry and seen as a fuel for shipping the future (IEA, 2019), while methanol is already used in mainly the chemical industry, and in the future maybe even more using "methanol-to-olefins[23]", while it also seen as a e-fuel in the transport sector.

In these sectors this study identifies two key points 1) the competitiveness with alternatives both low-carbon and fossil, and 2) a constant supply is a necessity. For the competitiveness with fossil-based/grey alternatives, incentives are needed to make hydrogen competitive and this is heavily dependent on government policy. This includes the already very significant EU Emissions Trading Scheme (EU ETS, 2017). IN the future this system will become more

[22] Average of IEA predictions 200-700 $/kW for different system sizes for Alkaline system for the long term (IEA, 2019)

[23] Olefins are input to crackers, such as Ethylene and Propylene, used in the production of plastics.

important with the rising carbon price and lowering of emission allowances and importantly the phasing out of the exemptions[24] for some sectors. The Dutch SDE system and the announced Carbon Contract for Differences for low-carbon hydrogen by the EC (Oxford Energy, 2020) also increases the potential of green hydrogen. Both are used to limit price gap and the unprofitable top margin for green hydrogen with its fossil-based alternatives. It should be noted that the recently announced, Dutch SDE++ also limits the subsidies for green hydrogen by maximizing load hours at 2000 to prevent the electrolysers from running on grey electricity, which would make carbon footprint of the produced hydrogen even higher than grey hydrogen (PBL, 2020).

6.3 The four hubs

In the hydrogen vision from the Port of Rotterdam (2020a), and in another recently published report from Drift (2020), four hubs are outlined to "*seize hydrogen opportunities*" – i) production, ii) import, iii) trading and iv) usage hub. These are partly based around the usual functions and income flows of the port, such as conversion in industrial complexes and throughput into the Hinterland, however, the question this section will answer is if the ambitious targets set out for these hubs align with the potential of hydrogen based on the learning curve principles, and thus, the findings from the previous chapter. First, table 7 shows an analysis of the potential of the four hubs.

Table 8: Potential of the four hubs

HUBS	Drivers	Enablers	Policy advice	Potential
Production	Offshore wind growth (Offshore) Integration electrolyser w/ RES	EU/National Policy (SDE, CCFD's and ETS).	Activate hub with blue hydrogen Incentivize industry to Decarbonise/ switch to H2	High after 2030
Import	Decrease in overseas transport costs	Hinterland pipeline infrastructure Industry switching to H2 (Usage hub)	Connect with RE abundant countries (see DE with Morocco) Invest in infrastructure	Low and Long term
Trading	Transport and conversion costs/efficiency Rise of other hubs	Hinterland pipeline infrastructure EU policy	Connect with RE abundant countries (see DE with Morocco) Invest in infrastructure	Low and Long term
Usage	LCOH decrease Increase CO2 price Constant supply of H2 Needs scale	EU/National Policy (SDE, CCFD's, and ETS) Increase NG price	Activate hub with blue hydrogen Incentivize industry to decarbonise/ switch to H2	High - scale up 2025

[24] Exemptions are made to prevent carbon leakage for sectors such as the steel and aviation sector; Including such sectors in the scheme would lead to production outside the EU, offsetting carbon emissions in other countries while losing businesses in the EU at the same time.

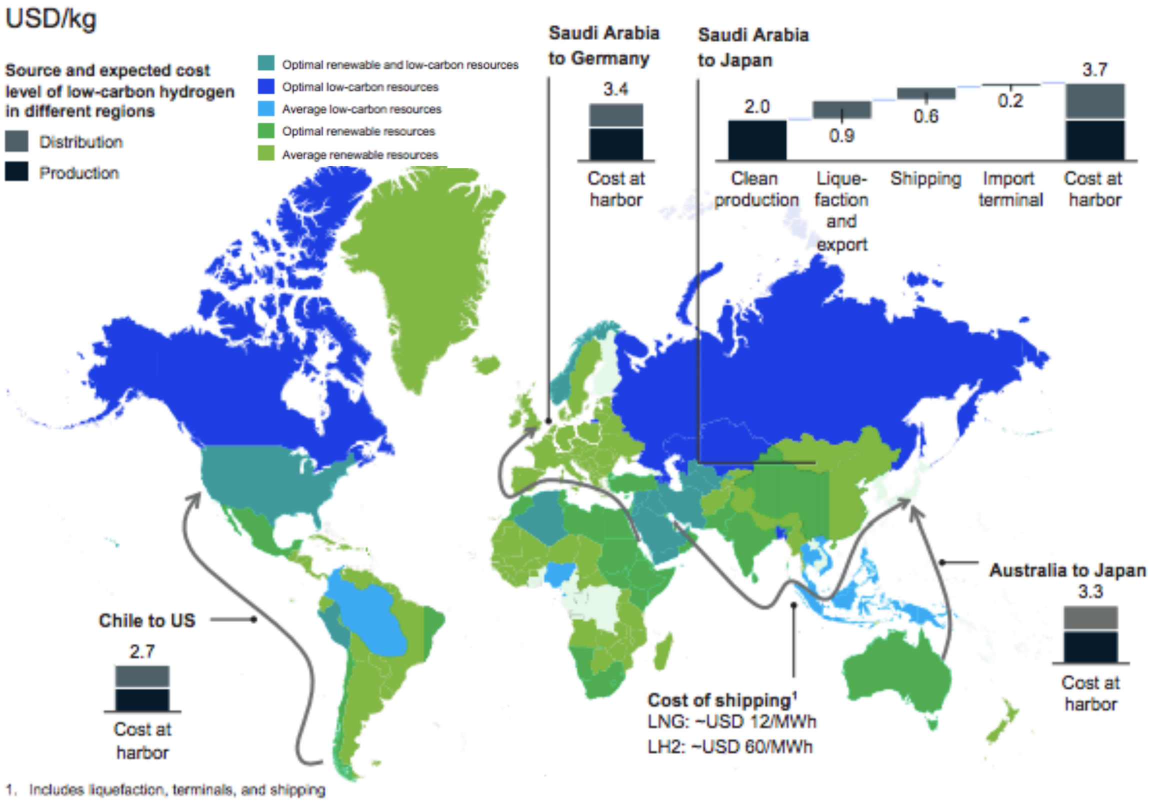
The varying learning rates, as mentioned before, show that the potential is constrained by electricity costs and load factor, leading to the different cases discussed to illustrate the derived learning rates. Below these cases are applied to the ambitions of the four different hubs, first the implications for the i) production hub of the results in the a) grid-connected and b) off-grid integrated cases are discussed, hereafter the implications for ii) import hub are discussed following the results in the c) large scale import case. Afterwards, the overall results are implied to the trading and usage hub, since both are dependent on the overall potential of the hydrogen, and on the other hubs.

In the grid-connected cases the low variable learning rates show a limited potential without substantial decreases in grid electricity prices or lower prices in the power purchase agreements (PPAs) the green hydrogen producer can negotiate. SOEL does initially show a higher ability to learn, which is applicable where steam is available and for the production of e-fuels, needing (air) captured CO_2. Both for the production of e-fuels and regarding steam availability, usage hubs or industrial clusters are already present in the port. In these industrial clusters, synergies using for instance the SOEL technology, are a way of offsetting the low overall learning rates of grid-connected green hydrogen. However, in these grid-connected cases electricity price remains key, together with share of green energy in the Dutch electricity system, as the hydrogen does need to be green. Hence in grid-connected cases, the carbon emissions abated need to be significantly high, or serving sectors which are harder to abate, such as aviation, shipping and in several industrial applications to claim the elsewhere much needed renewable electricity at a high load factor.

The off-grid integration case shows significantly more potential to learn, and therefore, this is also implied for the integration of green hydrogen production in the Port of Rotterdam with offshore wind in the North Sea. Moreover, in this way, green hydrogen production complements offshore wind by allowing higher overall energy production, providing seasonal storage and reducing grid connection costs. In a sense, green hydrogen can in this case be seen as a by-product of green electricity production and hereby, it does not compete for the renewable electricity still needed in the Dutch electricity mix. The previously mentioned crosswind project from Shell is an example, which actually uses the generated green hydrogen in one of Shell's refineries in the port of Rotterdam (Shell, 2020). This contradicts with the intentions of the Port of Rotterdam to dedicate 2 GW's of offshore wind capacity to the production of green hydrogen by 2030, however, in the further future a greener Dutch electricity mix allows for dedicated production, where nonetheless integration still can play a large role. Further research needs to be done into integration of green hydrogen production with offshore wind, possibly adding floating solar PV and batteries to further optimise in an extensive hybrid. Blue hydrogen can be used as an interim solution to start the hydrogen economy in the other hubs, allowing for infrastructure to be built and hydrogen knowledge and experience to accumulate and locally spill over to the learning rate of green hydrogen in the Port of Rotterdam. In this way, smaller integrated, and possibly subsidized, green hydrogen projects together with Blue Hydrogen can be seen as a first step to start the hydrogen economy in the Port of Rotterdam.

Large scale imports of hydrogen overseas compressed or in different liquefied forms through an import hub at the port can also provide for an alternative solution here, to provide cheaply produced green hydrogen. However, considering the recent publication from the Hydrogen Backbone (2020), pipelines can be seen as competition, providing for a cheaper solution compared to intercontinental import per ship. To illustrate, costs for transporting hydrogen from the south of Spain to Rotterdam by pipeline are under 0.40 €/kg of hydrogen (European Hydrogen Backbone, 2020), significantly less compared to the 1-1.5 €/kg stated by the Hydrogen Council (2020) in the figure below. With a hydrogen backbone, the target of the port of Rotterdam to replace oil imports by massive green hydrogen imports overseas is heavily impacted. The findings in this report showed how critical the input electricity is in terms of price and load factor, with low levels of levelized costs which can already be reached at large scale, which all the more make transportation costs relatively more important. Possible export worldwide routes are shown below in figure 7, where the colour of the countries show if the country's potential in terms of green or blue hydrogen production. For the port of Rotterdam specifically the route between Saudi-Arabia and Germany is of importance, where the Port Authority sees itself as importing green hydrogen, hereafter using the Hydrogen Backbone to transport it to Germany in a similar way the hinterland has been used. Hence, in this case a Hydrogen Backbone with pipelines enables hinterland transport in a similar way the waterways still do. The question is, however, if this is realistic given the various sun and wind abundant regions reachable by pipeline transport, highlighting again the high relative impact on the hydrogen price of transport costs in cases with low LCOH.

Figure 12: Transporting green hydrogen globally (US dollars per kg, in 2030)



Source: Hydrogen Council (2020)

Furthermore, as clearly visible in the oil industry, geo-political factors need to be considered. In typical oil-exporting countries, such as Saudi-Arabia, there will eventually come a need to diversify their usual fossil-based portfolio by producing low-cost green hydrogen, in a way to export abundant renewable energy, to countries such as Germany, which in the future is seen as an green energy importer. Moreover, new countries will emerge as green energy and hydrogen exporters, creating alternative and maybe even more preferable distribution channels, also dependent on the geo-political ties between countries. An example are the recent developments regarding Nord Stream 2, a gas pipeline through the Baltic sea connecting Russia with Germany, which has become a political minefield also involving the US protecting their gas exports to Europe (CNN, 2020).

It shows the complexity of predicting future import flows, which depends on a country's renewable energy potential, location and thus transportation options, geo-political factors and current energy mix. The current energy mix is of importance, because in countries and regions there may exists a need to first decarbonize before exporting green energy. This gives ground for extensive further research into the potential future import and-export flows of green hydrogen, combining these factors with the production costs analysis from this study. The foreseen role as trading hub follows from the import and conversion possibilities.

However, overseas hydrogen imports per ship via Rotterdam are, as discussed before, limited by transportation costs, while the possible conversion of hydrogen into liquid forms is logically done before transportation per ship. This makes the ambition to establish a large hydrogen trading hub converting and re-exporting hydrogen, similarly, as currently is done for crude oil, difficult to realise on the short-term. An option which can have more potential for an import hub in Rotterdam are to import a product (instead of a “gas”), for the transport sector, this could synthetic or electro fuels (e-fuels) or green methanol or ammonia, which both also have current and increasing potential in the industry. On the other hand, to form e-fuels CO_2 is needed, which is, similarly to hydrogen, also not easily transported overseas. CO_2 is expected to be available in port of Rotterdam with the planned CCUS infrastructure (Porthos, 2020), or even imported by pipeline from the port of Antwerp (Antwerp@C, 2020) or other industrial clusters. However, there is a difference between e-fuels using in this case CO_2 captured from an industrial process (CCS) or when CO_2 is captured directly from the air (direct air capture); only the latter is carbon neutral. This difference will show in the policy and subsidy systems, which e-fuels are reliant on.

Conclusion

This study, by using learning curve theory, expert elicitation and levelized costs, has concluded that the cost reduction potential for green hydrogen is higher and will come sooner than expected. This confirms the overall ambitions of the port of Rotterdam to start a hydrogen economy. However, by applying the results and learning rates to actual cases and zooming in on the different hydrogen hubs proposed by the port, challenges arise. Firstly, the limited availability and high price of local renewable electricity, at least on the short-term. Secondly, the relatively high costs of conversion and overseas transport of hydrogen, especially compared to transport by pipeline, hereby also making the comparison with the current oil business invalid. The first can be overcome by initially starting with the production of blue hydrogen. While on the other hand accelerating the deployment of offshore wind and moreover, electrolyser’ technological progress needs to focus on integration with renewables, to not further deflate green electricity demand, but rather complement the renewable energy source. The second challenge implies that the port needs to focus on importing and trading hydrogen-based products in liquid forms, like methanol, ammonia and synfuels, leaving import of gaseous hydrogen to pipelines. In conclusion, although the potential of green hydrogen is great, especially in the port of Rotterdam, it needs to be applied in the right ways which in the end benefit, and not hamper, a fast and low-cost road to carbon neutrality by 2050.

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